ANALYSIS OF TRUCKING VARIABILITY IN ROADWAY NETWORK ENERGY USING BASIC SAFETY MESSAGE DATA

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ANALYSIS OF TRUCKING VARIABILITY IN ROADWAY NETWORK ENERGY USING BASIC SAFETY MESSAGE DATA

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To my family

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LIST OF SYMBOLS AND ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
ASC	Actuated Signal Control
BSM	Basic Safety Message
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CSW	Curve Speed Warning
DSRC	Dedicated Short Range Communication
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
FSP	Freight Signal Priority
GDOT	Georgia Department of Transportation
GHz	Gigahertz
GPS	Global Positioning System
GVWR	Gross Vehicle Weight Rating
HC	Hydrocarbon
HGV	Heavy Grade Vehicle
HLDI	Highway Loss Data Institute
Hz	Hertz
I-SIG	Intelligent Traffic Signal System
LOS	Level of Service

MHz	Megahertz
MMITSS	Multi-Modal Intelligent Traffic Signal System
MOVES	Motor Vehicles Emission Simulator
MPG	Miles Per Gallon
NHTSA	National Highway Traffic Safety Administration
NO_x	Nitrous Oxide
NPRM	Notice of Proposed Rulemaking
NS3	Network Simulator 3
OBU	On Board Unit
PAMSCOD	Platoon-based Arterial Multi-modal Signal Control with Online Data
PM_{10}	Particulate Matter: 10 micrometers
$PM_{2.5}$	Particulate Matter: 2.5 micrometers
RFID	Radio Frequency Identification
RLVW	Red Light Violation Warning
RSU	Roadside Unit
RSZW	Reduced Speed Zone Warning
SAE	Society of Automotive Engineers
SPaT	Signal Phasing and Timing
SSGA	Stop Sign Gap Assist
SSVW	Stop Sign Violation Warning
SWIW	Spot Weather Impact Warning
TMC	Transportation Management Center

TSP	Transit Signal Priority
TTI	Texas Transportation Institute
UCR	University of California, Riverside
USDOT	United States Department of Transportation
UVA	University of Virginia
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
V2X	Vehicle to Everything
VOC	Volatile Organic Compound
VPISU	Virginia Polytechnic Institute and State University
VSP	Vehicle Specific Power
WAVE	Wireless Access in Vehicular Environments

SUMMARY

On September 14, 2017, the City of Atlanta cut the ribbon for the North Avenue Smart Corridor, which hosts a series of hardware designed to make the North Avenue corridor better designed and ready for connected and autonomous vehicles. For this corridor, researchers at Georgia Tech have begun the process of simulating connected vehicles and the communication between vehicles. This experiment is designed in such a way that this communication aspect need not yet be in place, as the data that is broadcasted in connected vehicles can be replicated through traffic simulators and communication network simulators. This experiment takes that replicated data and plugs it into an energy calculator in order to determine how the energy usage of a vehicle fleet changes as the truck percentage of the fleet changes.

This experiment began with the building of a microscopic simulation traffic model the North Avenue Corridor, modeling the signal timing, traffic volumes, and overall characteristics of all 19 signalized intersections within the three mile corridor. With this done, the model was run ten different times for each of seven different fleet compositions, each with a different percentage of single unit delivery trucks and tractor trailers. The data files directly outputted into VISSIM were then processed in such a way that they mimicked the standardized message broadcasted by connected vehicles. After this, the processed files were run through the energy calculator in order to determine the energy for each vehicle type as well as for the entire fleet.

From this experiment, it was determined that adding more trucks to a vehicle fleet has a small but definite change in the per-vehicle energy for passenger cars. The per-vehicle

change for trucks was larger than that of cars, but due to extreme variability in the truck results, the extent to which increasing truck percentage affects trucks is inconclusive. Future research into this topic should include much larger sample sizes than ten runs per fleet composition, and should include more fleet compositions in the range of 10% trucks to 50% trucks. These additions would give a clearer picture into the effect of truck percentage on energy. Future research may also include sampling the connected vehicle replica data to determine the expected sample error from various connected vehicle market penetration rates. This experiment as well as research that can build off of it help researchers test the capabilities and limits of the data that can be extracted from connected vehicles, allowing them to map out their benefits and drawbacks as they become a larger part of the nationwide fleet.

CHAPTER 1. INTRODUCTION

In March, 2017, the City of Atlanta announced the planning for the "North Avenue Smart Corridor," a plan to improve a three mile stretch of the city's North Avenue corridor with sensors, high definition cameras, and adaptive traffic signals with the capability to communicate with vehicles [1] [2]. Under the auspices of the 2015 Renew Atlanta Bond, the corridor is set up to eventually allow autonomous and connected vehicles to traverse this crucial artery [2]. As a corridor with industrial, residential, and high-density urban components, North Avenue's dynamic nature makes a good testing ground for these vehicles, as being able to traverse North Avenue sets autonomous and connected vehicles up for being able to drive on a wide variety of roads [1] [2]. On September 14, 2017, a demo, which included the testing of an autonomous vehicle, opened up the potential for Atlanta to become a leader in connected and autonomous vehicle research and deployment [2].

1.1 Project Background

As part of the city's endeavor to build this smart corridor, researchers at the Georgia Institute of Technology are working closely with the City of Atlanta and the Georgia Department of Transportation (GDOT) to simulate connected vehicles on North Avenue. One aspect of this effort involves using the microscopic traffic simulation software VISSIM to model 19 signalized intersections along the corridor, allowing researchers at the Georgia Institute of Technology to model travel times, vehicle trajectories, energy use, emissions, and other performance metrics on the corridor under different traffic conditions. A picture of the model can be seen below in Figure 1. In this picture, North Avenue can be seen running from top to bottom of the picture, with the Georgia Institute of Technology on the left side of the picture.

Figure 1: North Avenue VISSIM Model near Georgia Tech

1.2 Thesis Goals

Researchers at the Georgia Institute of Technology seek to use VISSIM to mimic the end result of the communication between vehicles and infrastructure. This can be done by using the files outputted by VISSIM to mimic messages sent from connected vehicles to other connected vehicles as well as the surrounding infrastructure. The experiment in this thesis focuses on this type of mimicked message. By using the mimicked message, the data in the message can be inputted into an energy calculator in order to determine the energy used by part or all of a vehicular fleet. The objective of this experiment is to use the mimicked connected vehicle message to determine how the energy usage changes alongside a changing fleet composition. Such a calculation could be done without mimicking the communication of connected vehicles, but by altering the standard data from

VISSIM into the standard message sent by connected vehicles, researchers will have a better understanding of the possibilities gained by using data extracted from connected vehicles. The energy usage will be analyzed to determine how changing the fleet composition by adding or removing trucks affects the overall fleet energy and as well as that of each individual vehicle type.

1.3 Thesis Organization

Following this introduction, Chapter 2 presents an overview of existing literature. This literature focuses on a basic overview of connected vehicles and their potential benefits as well as the disproportionally large role that heavy vehicles play in the energy use of the transportation sector in the United States. In addition, it discusses the software used to model traffic as well as the program used to calculate energy. Chapter 3 tells the methodology of the experiment, walking through the entire process from building the model to processing the results. Chapter 4 describes the results of the experiment, discussing what difference changing the fleet composition has on the energy use of different vehicle types as well as the overall fleet. Finally, Chapter 5 concludes the thesis, discussing what conclusions can and cannot be drawn from the results as well as the justification behind it. It also discusses limitations in the research and potential future research that can be explored both by using the framework from this experiment as well as moving beyond it.

CHAPTER 2. LITERATURE REVIEW

2.1 Microscopic Traffic Simulation Model

For this experiment, VISSIM version 9.00 was selected as the traffic simulation software. Developed in Karlsruhe, Germany, VISSIM is a microscopic and multi-modal software, and these aspects were critical in its selection. In a microscopic traffic simulator, the behavior of each vehicle can be individually analyzed. Using the car following models build by Professor Rainer Wiedemann in 1974, and 1979, VISSIM can simulate realistic driving behaviors such as braking, lane changing, and car following [3]. Its multimodality means that VISSIM can simulate interactions between several types of light and heavy-duty vehicles, bus and rail transit, cyclists, and pedestrians as they coexist in an urban environment.

VISSIM models settings such as vehicle behavior, fleet composition, roadway characteristics, and traffic control devices are input in to the model. When the simulation is initiated, vehicles are generated and travel through the network using the characteristics with which they were defined. As they travel through the network, various data can be recorded. Travel times and traffic volumes can be recorded for roadway segments and points respectively. Additionally, nodes, which are drawn around intersections, can collect volume and delay data to calculate the Level of Service (LOS) for intersections. The largest output is the vehicle record file, also known as the trajectory file. The vehicle record outputs pre-selected attributes such as vehicle number, speed, acceleration, and position for every vehicle at a pre-determined output which can be as frequent as every 0.05 second.

It is data from this file that can be fed into energy models to determine energy use data for a network.

2.2 Energy and Emissions

Transportation plays a large role in the energy usage and emissions generation of the United States [4] [5] [6]. In 2015, the Environmental and Energy Study Institute estimated that the transporting of goods and people accounted for 70% of all U.S. oil use, which comes out to over 13 million barrels of oil per day. Transportation also accounts for 1.8 trillion tons of greenhouse gases (GHGs) per year, which is 27% of the total GHG emission in the United States, second only to electrical generation [4] [5]. At 95.1% of transportation GHG emission, CO_2 plays the largest role of any GHG in the transportation sector [6]. As a GHG, CO_2 plays a large role in trapping heat within the earth's atmosphere, resulting in a warmer planet (NASA). The CO_2 concentration in the atmosphere has recently passed a threshold of 400 ppm, making the effects of climate change all but bound to happen (NASA). These factors make monitoring the energy and emissions of the transportation sector paramount

2.2.1 Heavy Vehicle Energy and Emissions

Within transportation, heavy vehicles can play a disproportionately high role in energy usage and emissions generation [4] [6]. Medium and heavy duty trucks account for over 20% of GHG emissions in the transportation sector while only making up 5% of the nationwide vehicle fleet [4]. This is due to two reasons. as they are driven commercially for longer periods of time, medium and heavy duty trucks are driven much further than passenger cars and light trucks. In addition, medium and heavy duty trucks emit more GHG and use more energy per mile compared to passenger cars and light duty trucks [4] [7] [8] [9]. According to the United States Environmental Protection Agency (USEPA), the CO_2 emissions factor per vehicle mile is 1.456 for medium and heavy duty trucks and 0.368 for passenger cars [7] [8]. Direct comparisons for other GHGs can be seen below in Table 1 and Table 2 [10] [11]. In these tables, it can be seen that diesel powered heavy duty vehicles emit pollutants at a higher per-mile rate than passenger cars. For this study, no gasoline powered heavy duty vehicles are studied or modelled, and as such, its emissions rates can be ignored. The wide disparity in fuel economy between cars and trucks reinforces their varying environmental impacts [12]. As of June 2015, passenger cars had an average fuel economy of 23.41 miles per gallon (mpg) compared to delivery trucks and heavy duty tractor trailers, with fuel economies of 6.64 MPG and 5.29 MPG respectively [12].

Table 1: Average Emissions and Fuel Consumption for Heavy Duty Vehicles (gram/mile) [10] [11]

Pollutant	HDGV (gasoline)	HDDV (diesel)
VOC	1.586	0.447
THC	1.635	0.453
CO	13.130	2.311
NOx	2.914	8.613
$PM_{2.5}$	0.044	0.202
PM_{10}	0.051	0.219

Table 2: Average In-Use Emission Rates for Passenger Cars [10] [11]

Pollutant/Fuel	Emission & Fuel Consumption Rates (per mile driven)	Calculation	Annual Emission & Fuel Consumption
VOC	1.034 grams (g)	(1.034 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	27.33 lb
THC	1.077 g	(1.077 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	28.47 lb
CO	9.400 g	(9.400 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	248.46 lb
NOx	0.693 g	(0.693 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	18.32 lb
PM_{10}	0.0044 g	(0.0044 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	0.12 lb
$PM_{2.5}$	0.0041 g	(0.0041 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	0.11 lb
CO_2	368.4 g	(368.4 g/mi) x (12,000 mi/yr) x (1 lb/454 g)	9,737.44 lb
Gasoline Consumption	0.04149 gallons (gal)	(12,000 mi/yr) / (24.1 mi/gal)	497.93 gal

In addition to the increase in fuel usage and GHGs when moving from passenger cars to heavy duty trucks, there has been a noticeable increase in fuel usage and GHG emissions within the heavy-duty truck category over the last 20 years [6]. From 1990 to 2005, the total GHG emissions from trucking have increased by over 60%, despite the emissions by water, rail, pipeline, and air remaining largely flat over the same amount of time [6]. This is due to a large increase in total trucking in ton-miles in that same time frame, but can also be attributed to a 12% drop in efficiency [6]. This increase in trucking GHG emissions combined with increasing needs to reduce it makes being able to monitor trucking's environmental impact of paramount importance.

2.2.1.1 Variability in GHG Emission Rates

In addition to having larger GHG emissions when compared to passenger cars, heavy duty vehicles also have a larger variance in emissions [13]. This is due to the wide variety in types of heavy vehicles currently deployed in the United States. Currently, trucks are split into eight classifications based on their Gross Vehicle Weight Rating (GVWR), which is the maximum allowable weight that a vehicle of that class is designed for and allowed to carry [14]. The classifications can be found below in Table 3. These classifications make it important to define what is considered to be a heavy vehicle. The emissions rates found in Table 1 were calculated using a weighted average of all eight classifications found in Table 3, while oftentimes Class 7 and Class 8 trucks are put into their own category of Heavy Duty Trucks, as they require a special Class B Commercial Driver's License to drive them [10] [14].

Table 3: US Commercial Motor Vehicle Classifications

Classification	Minimum GVWR (lb)	Maximum GVWR (lb)
1	0	6,000
2	6,001	10,000
3	10,001	14,000
4	14,001	16,000
5	16,001	19,500
6	19,501	26,000
7	26,001	33,000
8	33,001	80,000

The VTT Technical Research Centre of Finland undertook a three-year study to understand the different factors behind the variability in commercial truck fuel usage [15]. The study found that the primary factor behind fuel consumption is the vehicle's mass [15]. It is also the driving force behind changes in GHG emissions. PM and NO_x were particularly dependant on weight, varying by a factor of 4 and 2.5 respectively between two of the vehicle types tested. These differences are not too surprising, as truck weights in the United States could differ by as much as 74,000 lb. The emission calculations from Table 1 broken down by vehicle classification can be found below in Table 4. In this table, the pollutant rates overall increase from Class II to Class VIII, displaying how weight can affect GHG emission rates. What was surprising was the variance in fuel use between trucks of the same vehicle classification, which could vary by as much as 16% [15]. This variability can potentially be attributed to the significant differences in weight within the same vehicle category, which in the United States is especially prominent for Class 8 trucks.

Table 4: Average Heavy-Duty Truck Emission Rates by GVWR Class (gram/mile) [10]

Pollutant	Fuel	IIb	III	IV	V	VI	VII	VIIIa	VIIIb
VOC	gas	1.353	1.667	4.234	2.632	2.477	2.857	3.628	(1)
	diesel	0.189	0.201	0.262	0.274	0.365	0.453	0.455	0.545
	gas	1.400	1.713	4.319	2.693	2.535	2.920	3.704	(1)
	diesel	0.194	0.204	0.266	0.278	0.370	0.459	0.461	0.552
CO	gas	11.220	15.810	33.860	19.580	18.130	23.130	28.560	(1)
	diesel	0.839	0.908	1.163	1.189	1.367	1.719	2.395	3.109
NOx	gas	2.734	2.920	4.133	3.735	3.650	4.199	4.892	(1)
	diesel	3.088	3.298	4.352	4.548	5.990	7.471	9.191	10.990
PM2.5	gas	0.043	0.045	0.058	0.046	0.045	0.046	0.049	(1)
	diesel	0.091	0.073	0.089	0.079	0.172	0.177	0.215	0.238
PM10	gas	0.049	0.051	0.074	0.055	0.054	0.056	0.061	(1)
	diesel	0.099	0.079	0.096	0.085	0.186	0.192	0.233	0.259

Variability in truck fuel usage and GHG emissions can be attributed in smaller part to other factors in additional to mass. Long-haul freight trucks typically idle for at least 2,000 hours per year in order to house drivers while they sleep [16]. This idling consumes almost one billion gallons of fuel and emits 11 million tons of CO_2 per year in the United States alone [16] [15]. Idle reduction technologies have the potential to lower the per-hour fuel usage and electrical load needed to house drivers while trucks idle, reducing its environmental impact. In addition to idling, the type and conditions of the roadway affect fuel usage and GHG output. Fuel usage and GHG output tend to increase as the LOS worsens [13]. These factors can also increase when moving from a freeway to an arterial setting [13]. This is due to a change in how energy is lost when transitioning from city roads to a limited access highway. On a highway, aerodynamic losses account for 15-22% of energy loss, while inertia and braking account for 0-2% [17]. On city roads, these numbers change to 15-20% and 4-10% respectively, as trucks must stop more and travel slower than those on highways, resulting in less aerodynamic loss [17]. These differences show the importance of modelling realistic truck and roadway types when modelling a corridor to measure emissions and energy.

2.3 MOVES-Matrix

The MOVES-Matrix was created by professors and engineers at the Georgia Institute of Technology in order to more efficiently measure the energy and emissions data of a roadway network.

2.3.1 The MOVES Model

The EPA created the MOtor Vehicles Emission Simulator (MOVES) to estimate US vehicle emissions [18]. Its creation was an improvement over the previous simulator, MOBILE 6.2, as the latter failed to take into account a vehicle's acceleration [18]. Instead, vehicular speed was the defining attribute by which energy and emissions data were generated. Acceleration is a large contributor to energy and emissions outputs, and it was paramount that this factor be reflected. The MOVES Model solved this issue by putting vehicles into different bins based off of their speed, acceleration, and vehicle type [18].

These data are inputted in second-by-second format. In the current study these will be taken from traffic simulation output files such as VISSIM's vehicle record files [18]. Adjustments are also made for factors such as temperature, humidity, and age distribution of the fleet. The inclusion of these factors allows the model to output more precise data for a variety of conditions [18]. When these adjustments are made, emission and energy rates for that second can be calculated for each vehicle, link, and the overall network. The full data process can be found below in Figure 2 [18].

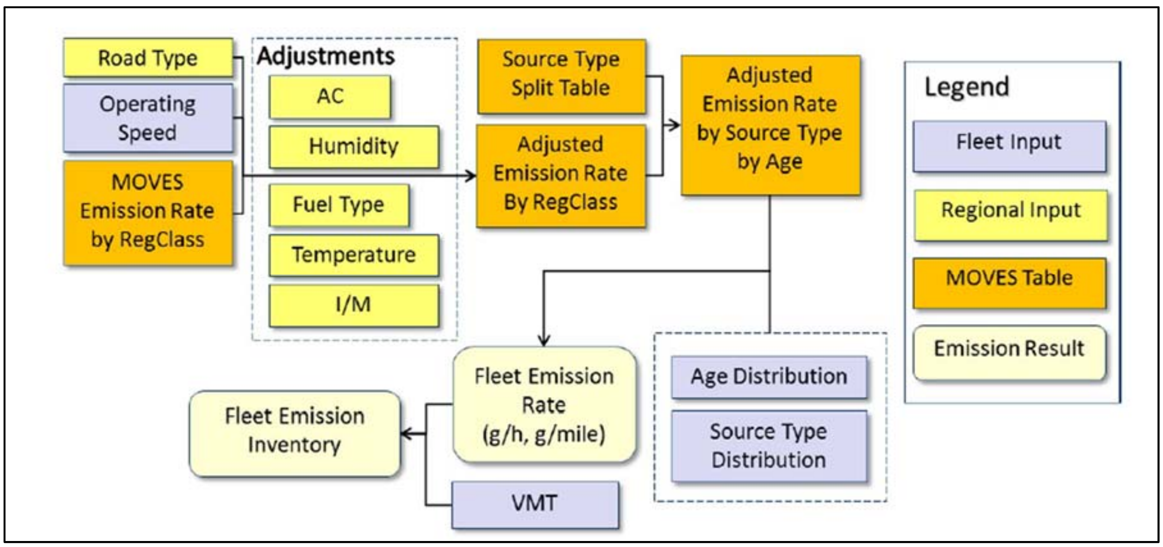

Figure 2: MOVES Data Processing [18]

The accuracy of the MOVES model comes at a cost. The addition of factors into the model means the interface is complex. Additionally, the run times are lengthy, making real time emissions analysis impossible. The potential variation in humidity, temperature, and other factors means that there are too many individual MOVES runs required to feasibly measure a network's energy and emissions output over a long period of time [18].

2.3.2 MOVES-Matrix

To streamline the process, a research team at Georgia Tech created the MOVES-Matrix. This Matrix can be used to find the energy and emissions results in a small fraction of the time it would take the MOVES model [18]. The Matrix can do this because it the result of 146,853 MOVES runs under various conditions. Because of this, factors such as temperature, humidity, model year, and fuel type are pre-loaded into the matrix. Instead of having to adjust for those factors, the user can simply select the sub-matrix for the conditions he or she is testing [18]. The Matrix runs 200 times faster than the MOVES GUI, allowing for real time energy and emissions data output. At the same time, because the Matrix is a collection of pre-run MOVES GUI models, the end result of using the GUI and Matrix is exactly the same [18]. Figure 3 below shows the data processing overview for the MOVES Matrix [18]. The MOVES-Matrix calculates a vehicle's power for each second using its speed, acceleration, and the roadway grade [18]. With this Vehicle Specific Power (VSP), vehicle speed, and vehicle acceleration, the vehicle is placed into an operating bin. For each vehicle type, energy and emissions rates are assigned to the vehicle for that second [18]. These data can be added together in order to obtain emissions data anywhere from one vehicle to an entire fleet. The increase in the number of factors included in the Matrix results in a streamlined process that allows emissions data to be much more efficiently found.

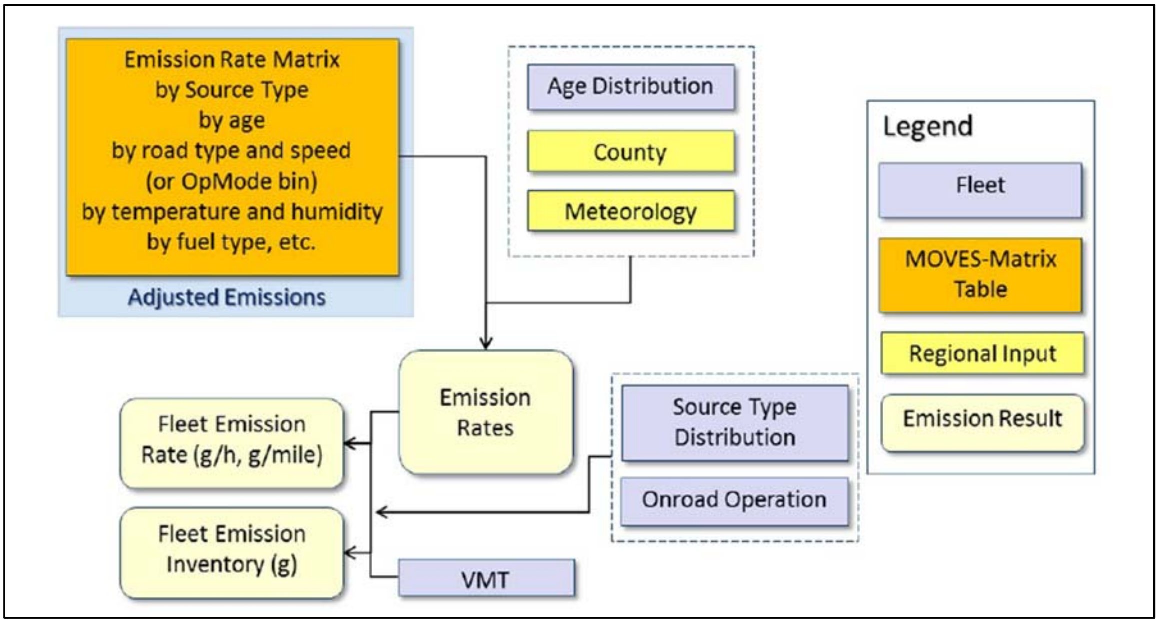

Figure 3: MOVES Matrix Data Processing Overview [18]

2.4 Connected Vehicle Technology

Connected vehicles are vehicles that are equipped to generate data about themselves and share and exchange it. This exchange can happen with other equipped vehicles or with properly equipped infrastructure such as traffic signal controllers [19].

2.4.1 Vehicle to Everything (V2X)

V2X can be broken down into two parts. The first, Vehicle to Vehicle (V2V) communication, shares data between vehicles. This data can be used to warn drivers about potential collisions with other vehicles [20]. This is done by broadcasting vehicular data such as position, velocity, and acceleration to surrounding vehicles ten times per second. The second, Vehicle to Infrastructure (V2I) communication, shares data between vehicles and the surrounding infrastructure. As with V2I, this data can be used to prevent collisions between vehicles or between vehicles and infrastructure. Additionally, this data can be used to improve operational elements of the road by reducing overall travel time and emissions outputs [20].

Both V2V and V2I require communication equipment inside vehicles, known as On Board Units (OBUs). This may include but is not necessarily limited to a communications radio, data storage components, a Global Positioning System (GPS) Receiver, and a Driver-vehicle interface [21]. V2I communication requires additional connected infrastructure. Roadside equipment, commonly known as Roadside Units (RSUs), receive information from connected vehicles and communicate with the traffic signal controller to broadcast Signal Phasing and Timing (SPaT) data to the vehicles. Also needed are a back office such as a state Transportation Management Center (TMC) and proper backhaul wiring to transmit data from the RSUs to the TMC [20]. A typical V2I equipment setup can be found below in Figure 4 [20].

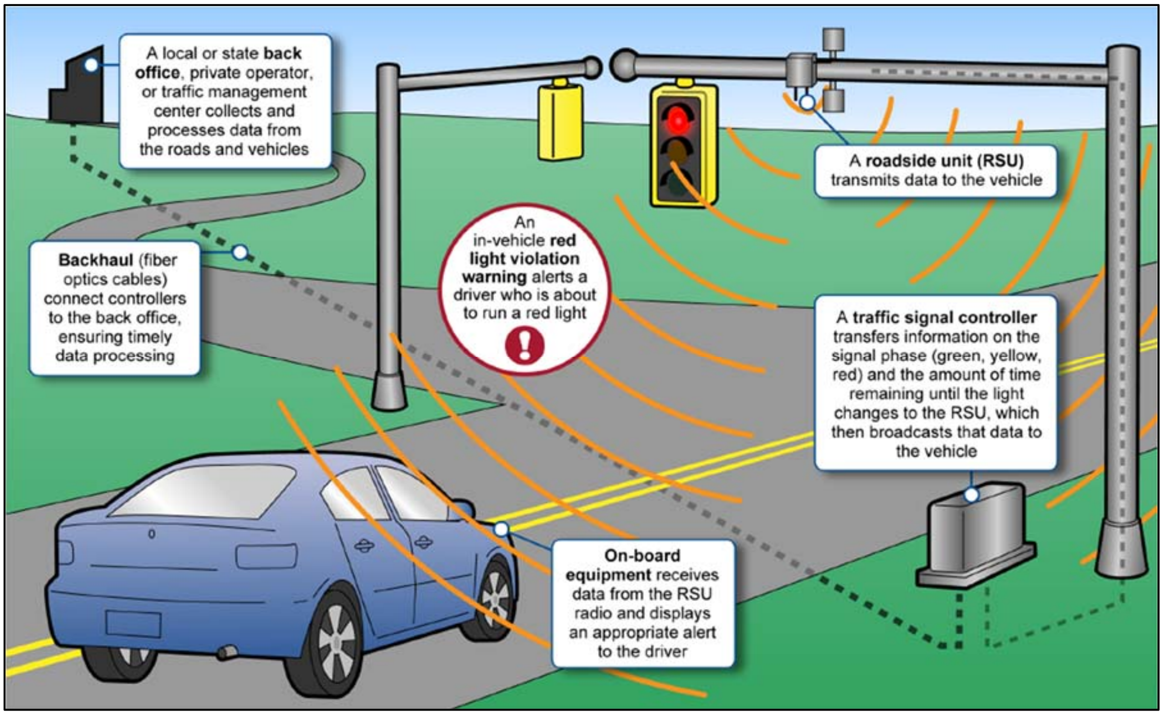

Figure 4: V2I Example Intersection [20]

Although the above figure shows V2I communication at an intersection, it is not limited to this scenario. V2I applications can be used on roadway corridors in between intersections, in work zones, and even at railroad crossings [20] [22] [23].

2.4.2 V2X Communication Technology

Two types of wireless communication technologies are typically considered for V2X applications: cellular technology and Dedicated Short Range Communication (DSRC) for Wireless Access in Vehicular Environments (WAVE). Cellular technology is not a strong contender compared to DSRC as the latter has lower latency and is designed specifically for V2X applications [19]. DSRC also has a dedicated spectrum from the Federal Communications Commission (FCC) of 75 megahertz (MHz) from 5.850 to 5.925 gigahertz (GHz). This dedicated spectrum allows for higher reliability of DSRC over cellular technology at a typical range of 300 meters [20] and a maximum range of 1,000 meters [24]. For these reasons, the United States Department of Transportation (USDOT) has made DSRC the designated communications technology for vehicular communication research [20].

2.4.3 The Basic Safety Message

The content of the message broadcasted from vehicles to infrastructure and other vehicles has been standardized. The Society of Automotive Engineers (SAE) standard J2735 established the Basic Safety Message (BSM) as the standardized message that provides all information needed for safety and operational V2X applications [24]. The BSM consists of two parts. Part 1 is mandatory for all equipped vehicles, and includes core elements such as speed, acceleration, brake status, and vehicle size to be sent out at a constant rate of ten times per second [24]. Part 2 is a much more extensive list of optional data elements, such as ambient temperature and pressure, the status of windshield wipers, and tire conditions [24]. Unlike Part 1's strict 10 times per second frequency requirement, Part 2 data elements can be sent out at various frequencies or are only sent out when triggered by certain events [24].

In order for VISSIM to be able to mimic the BSM, it must be able to output all data elements from Part 1. Elements of the Basic Safety Message can be found in the VISSIM Vehicle Trajectory files in three different ways. Some elements, such as elevation, speed, and acceleration, can be directly output via VISSIM's Vehicle Record. These elements may also be directly converted into the proper format, such as the X/Y position in VISSIM being converted to lat/long for the basic safety message. Other elements, such as brake system status and, must be assumed based on Vehicle Record attributes such as deceleration. Finally, elements such as the heading and yaw rate can be calculated using other attributes of the Vehicle Record. The former can be calculated by using the coordinates of the front and back of the car, and the latter can be calculated by measuring the rate of change of the heading. Table 5 below lists all data elements from Part 1 as well as in which of the three categories they belong.

Table 5: BSM Part 1 Attributes and Their Collection Type

BSM Part 1 Attribute	Data Gathering Category
Latitude	Directly Outputted
Longitude	Directly Outputted
Elevation	Directly Outputted
Positional Accuracy	Directly Outputted
Transmission State	Assumed
Speed	Directly Outputted
Heading	Calculated
Steering Wheel Angle	Calculated or Assumed
Longitudinal Acceleration	Directly Outputted
Lateral Acceleration	Directly Outputted
Vertical Acceleration	Directly Outputted
Yaw Rate	Calculated
Brake Status	Calculated
Vehicle Width	Directly Outputted
Vehicle Length	Directly Outputted

2.5 V2I Communication Benefits

V2I benefits can be broken into two categories. The first is safety, with applications that help prevent collisions due to aspects such as running red lights, drifting out of a lane, and severe weather. The second is operations and emissions, with applications designed to minimize travel time, energy used, and emissions generated by a vehicle.

2.5.1 Safety Benefits

DSRC is one of the central parts of the connected vehicle safety programs. Its low latency is critical for safety applications, and is one of the major reasons why DSRC was designated as the V2X communication technology over cellular technology [20]. Several applications have been identified by the Federal Highway Administration (FHWA) for further research. These applications are designed to prevent crashes at intersections, on curves, on roadways affected by severe weather, and due to hard braking by vehicles.

2.5.1.1 Intersection Safety

Every year in the United States, up to 575,000 crashes and more than 5,100 fatalities occur at intersections [25]. Many of these crashes are caused by driver errors that can be mitigated against using connected vehicle technology. Red Light Violation Warning (RLVW) and Stop Sign Violation Warning (SSVW) work to prevent crashes in intersections by warning vehicles approaching an intersection if they are about to pass through the intersection while being given a red light or without having sufficiently stopped at a stop sign [25]. They work by linking the RSU to the signal controller and sending SPaT data to the vehicle so that the driver may receive earlier knowledge of the current signal phasing [25]. The RSU also receives the BSM from the vehicles, and by looking at their speed, acceleration, and distance to the traffic signal or stop sign, can warn the driver of a potential conflict [25]. These applications combined have the potential to address up to 279,000 crashes and 2,800 fatalities per year [25].

Stop Sign Gap Assist (SSGA) works to warn drivers of conflicts when traversing stop controlled intersections [25]. When at a minor street, a driver turning may misjudge the distance between them and an approaching vehicle. The application works by using an RSU to gather BSM data from all vehicles in or near the intersection, analyze vehicular location and speed, and inform drivers waiting on the minor street whether or not the gap between vehicles is safe [25]. This application has the potential to address up to 279,000 crashes and 1,400 fatalities per year, and has already been found to reduce the risk level and give clear instructions to drivers in a test study [25]. Clarity of message is important in connected but non-autonomous vehicles, as they must be understood quickly by drivers that may be in a high stress driving environment.

Pedestrians are very vulnerable in intersections, and must hope drivers notice them when crossing the street. The Pedestrians in Signalized Crosswalk assists drivers in detecting pedestrians to prevent a potential crash and severe injury or fatality [25]. The RSU can send a caution message to vehicles approaching the intersection when the pedestrian push button has been pressed, and send a warning when a pedestrian has been detected in the crosswalk [25]. This system has seen some success in initial testing, and further development is being considered in the timing of the warning. During initial testing, warnings were sent to vehicles that were not yet approaching the intersection. Tailoring the timing of the warnings so that they are only received by vehicles approaching the intersection while still giving drivers enough time to react and stop is an important improvement that must be made in future research.

2.5.1.2 Curve Safety

V2I benefits are not limited to intersections. As dangers are also present when traveling between intersections, safety applications can be developed to mitigate against them. If traveling too fast, roadway curves can be deadly to vehicle occupants [25]. Distracted drivers may enter a curve driving faster than they realize, and the Curve Speed Warning (CSW) system is being developed to warn drivers to slow down. The CSW works by the RSU collecting BSM data from vehicles approaching the curve. By analysing attributes such as location, speed, and brake status, and with knowledge of the curve's radius, superelevation, and safe speed range, the RSU can warn the driver if it appears that they will enter the curve at an unsafe speed [25]. During redeployment of the initial testing, drivers were seen traversing the curve at lower speeds and overall less aggressively when warned by the CSW, and drivers were overall responsive to the alerts. When working properly, the CSW has the potential to address up to 169,000 crashes and 5,000 fatalities every year [25].

2.5.1.3 Weather Safety

While curves are a constant presence to be warned against, the dangers of severe weather are not always on the road. Fog, ice, and water on the road are severe dangers that cannot always be seen by even the most attentive of drivers. The Spot Weather Impact Warning (SWIW) is a concept by which RSUs can warn drivers if they are approaching a severe weather danger on the roadway. These dangers could be broadcasted to the RSU itself through sensors on the road that measure temperature or moisture content, roadway cameras, or through information received at a DOT office or TMC. Although this application is still only a concept, it has been shown to have the potential to reduce crashes during winter weather by up to 25% [25].

2.5.1.4 Hard Braking Prevention

A key element in reducing rear end collisions is the prevention of and warning drivers about the sudden appearance of reduced speed zones. These reduced speed zones can happen seemingly without warning, and can take even undistracted drivers by surprise. The Reduced Speed Zone Warning (RSZW) helps mitigate against these crashes by detecting reduced speed zones through analysis of BSMs and warning drivers approaching the reduced speed zone of the upcoming slow down. This can be applied for general traffic congestion, but can also be used to great effect at roadway work zones [25].

In a field test run by Maitipe et al, a combination of V2V and V2I was used to calculate the expected travel time, starting location, and ending location of the construction congestion and broadcast that to approaching vehicles [23]. The range of the broadcast was amplified by using V2V technology to relay the message from vehicle to vehicle. This allows the range of the message to extend beyond the start of the congestion, allowing the application to be feasible. The starting location of the congestion was found by setting a certain percentage of the posted speed limit as the threshold for when congestions was considered to have started [23]. The message relay system was designed so that the message would only be passed to the farthest OBU in range of the relaying vehicle, minimizing the number of messages as well as the risk for message congestion or loss. The relay also used angular and back-propagation checks to ensure the message is sent in the correct direction. At a demonstration site in Duluth, Minnesota, the RSUs were able to measure travel time and the starting location of construction [23]. Additionally, the message relay system increased the range of broadcast from 300 meters to over 1,400 meters, with longer distances suspected to be possible given higher amounts of OBU equipped vehicles [23]. This technology can feasibly be used to protect vehicles from accidents due to hard braking as well as protect construction workers from distracted drivers unaware of the construction zone they are approaching.

Advanced warning systems are also viable at rail crossings. RSUs near at-grade rail crossings can give drivers advanced warnings of approaching trains in addition to existing signage or cantilever systems in place. In a German study done with a Volkswagen T5 and an train equipped with OBUs as well as an RSU at the crossing, the concept of adapting V2X technology for Rail2X applications were found to be feasible [22].

2.5.2 Operational and Emission Benefits

Per the Texas Transportation Institute (TTI), drivers in the United States wasted 6.9 billion hours and 3.1 billion gallons of fuel due to roadway congestion in 2014 alone [25] [26]. Connected vehicle technology has the potential to lower travel times on roadways by minimizing the number of stops and slowdowns that vehicles must go through [25]. This minimization has the added benefit of reducing tailpipe emissions, as fewer stops and slowdowns means fewer accelerations that burn more fuel and emit more pollutants [25]. The connected vehicle applications aimed at improving operations and emissions can be generally broken down into two categories. The first sends SPaT and other data through an

RSU to vehicles in order to adapt their speed and acceleration under the given conditions. The second sends BSM data to infrastructure such as an RSU connected to an intersection's signal controller in order to adapt the phasing and timing of the signals.

2.5.2.1 Adaptive Vehicle Control

Adaptive vehicle control works to minimize delay and emissions by optimizing vehicle speeds given the existing infrastructure conditions. This can be done by sending SPaT data from an RSU and signal controller to a vehicle approaching an intersection. By knowing the signal's phasing and timing data, the vehicle can calculate the vehicular velocity that will allow the vehicle to reach the stop bar at a coasting speed exactly when the signal changes from red to green or allow for the vehicle to come to a stop in the most eco-friendly way [25] [26]. In addition to optimizing approaches and departures at intersections, connected eco-driving allows RSUs to use advanced knowledge of the roadway to inform vehicles of optimal speeds and accelerations ad the vehicle interacts with changes in grade, terrain, traffic conditions, and surrounding vehicles. This improves vehicular mobility by enabling the vehicle to potentially leave the intersection already in motion as opposed to having to start again after coming to a complete stop. By reducing the amount of time needed to accelerate, this also reduces the energy usage and emissions output of the vehicle.

In a study completed by Haitao Xia et al., an eco-approach traffic signal application was created and tested in order to understand its potential benefits under a variety of conditions [27]. In addition to analyzing SPaT data, this enhanced system also analyzed the information of preceding equipped vehicles. This enhancement allowed for improved vehicular trajectory planning. Only analyzing the SPaT data assumes that the traffic conditions allow for a vehicle to accelerate or decelerate to its new speed [27]. By incorporating the trajectory data of preceding vehicles and finding the queue length and any potential congestion, vehicles can be guided through the intersection with a speed that can be maintained given the conditions at the time. The environment was simulated with the microscopic traffic simulator Paramics, and the application was tested under three different traffic demands and five different connected vehicle penetration rates [27]. The application was also test with and without consideration of preceding vehicles.

The fuel savings without and with considering preceding vehicles and intersection delay can be seen below in Figure 5 and Figure 6 respectively [27]. The results show a decrease in fuel usage under all tested conditions, with a decreasing rate of fuel reduction as the penetration rate increases [27]. The difference in fuel savings between the application with and without intersection delay consideration line up with original expectations. When traffic demand is low, there is little to no intersection delay to take into consideration, and the difference in fuel savings is negligible or non-existent. As the demand rises, considering intersection delay results in much larger increases in fuel reduction. With 600 veh/lane/hr and 100% penetration rate, fuel savings jump from approximately 27% without intersection delay consideration to approximately 37% with consideration [27]. This is the most extreme example under the most extreme condition, but still demonstrates the benefits of enhancing the eco-approach application. Although this study does not measure changes in operation, as mentioned previously, it is a safe assumption that reductions in fuel, energy, and emissions will also result in a reduction in travel time [27].

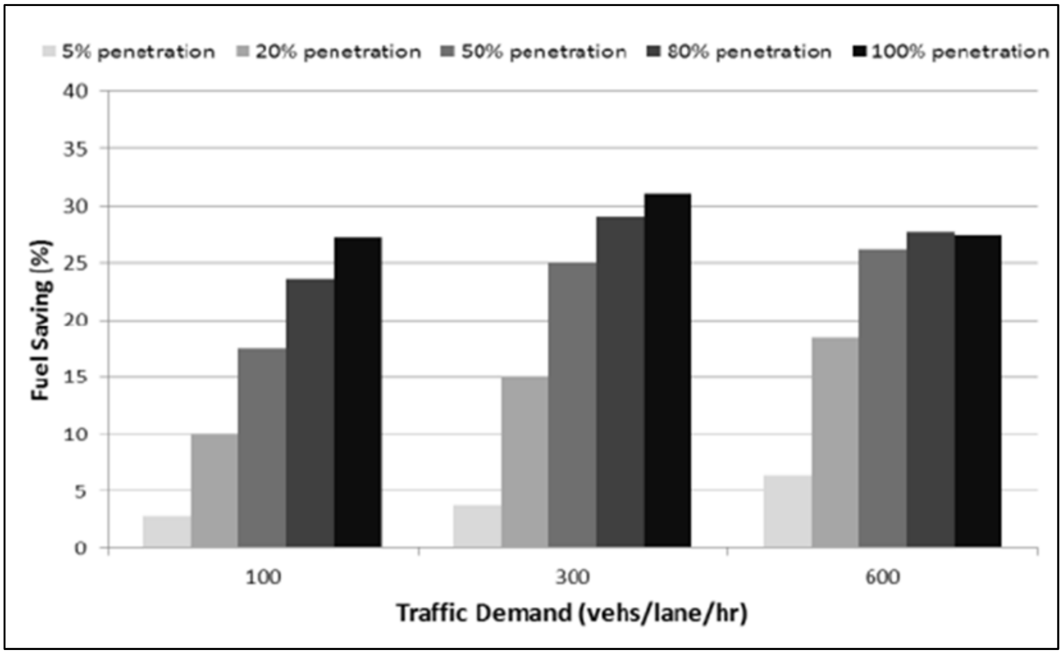

Figure 5: Eco-Approach Fuel Savings without Intersection Delay Consideration [27]

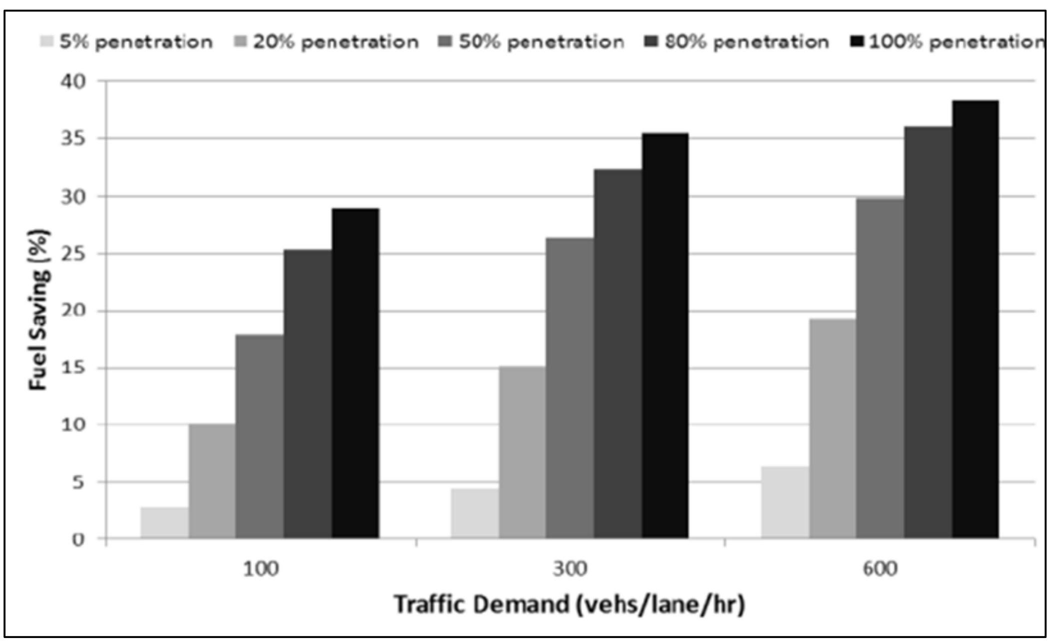

Figure 6: Eco-Approach Fuel Savings with Intersection Delay Consideration [27]

Data sharing with connected vehicle technology can also adapt vehicle paths before a trip begins. A V2I system can detect congestion and monitor traffic conditions using real time operational and emission data to advise drivers of the fastest and most eco-friendly route. This data can also be used to predict traffic conditions based off on existing and previous conditions. The work zone and railroad V2X applications mentioned in section 2.5.1.4 can also be applied to these traveller information systems [22] [23]. Drivers can receive advanced warning of construction induced congestion or current or future at-grade rail crossing closures due to rail activity. This routing has additional potential to optimize routes for emergency vehicles, where reducing travel time is of paramount importance.

2.6 Implementation

Currently, connected vehicle enabled corridors are almost always confined to test beds or field tests. Systems also exist in confined roadway networks such as seaports. The port of Hamburg, Germany deployed an intelligent traffic signal system in June 2015. This system uses wireless communication and radio frequency identification (RFID) to monitor truck traffic throughout the port [32] [33]. The system, conceptually similar to systems mentioned in section **Error! Reference source not found.**, involves RSUs monitoring for and communicating with platoons of trucks moving into and out of the port. The system can then adjust the SPaT in order to minimize CO_2 and NO_x emissions [32]. This is part of the Port of Hamburg's larger strategy to reduce emissions and improve overall port capacity through ITS technology [34].

2.6.1 Projected Penetration Rates

As connected vehicle technology advances, implementation will not happen overnight. Various estimates put equipping signals and vehicles with connected vehicle technology as taking multiple decades [35]. The American Association of State Highway and Transportation Officials (AASHTO) estimates that by 2040, 90% of vehicles will be equipped with DSRC [20]. A similar time scale is expected for the equipping of traffic signals with RSUs and other needed connected vehicle infrastructure. AASHTO estimates that 20% of intersections will be properly equipped by 2025, and 80% will be equipped by 2040 [20]. Figure 7 below shows a projection from a 2008 USDOT report of the penetration rate of DSRC in light fleet vehicles [36]. The projection shows a slowdown in the increase in penetration at approximately 80% penetration. This is due to the percentage of the light vehicle fleet over 20 years of age. Owners of these vehicles will be the last to purchase new vehicles that are DSRC equipped, delaying complete market penetration [36].

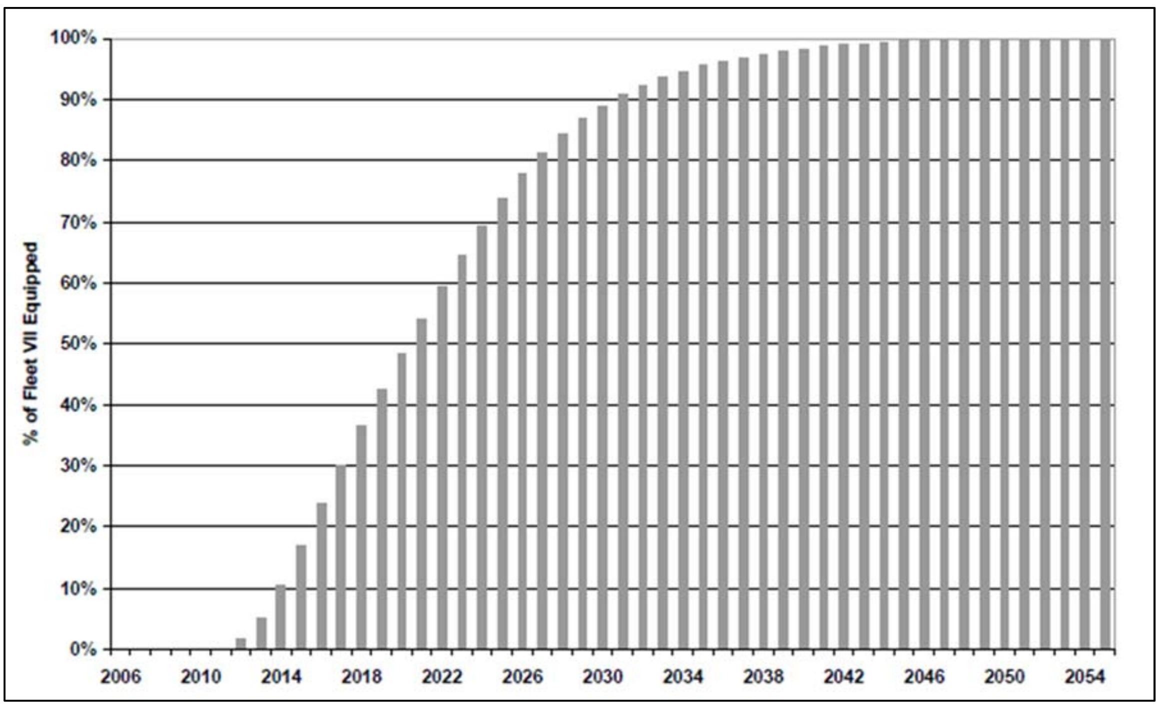

Figure 7: V2I Fleet Penetration in Light Vehicles [36]

Penetration rates for heavy vehicles has the potential to take place on a different timeline than that of light vehicles. Penetration rates for heavy vehicles may increase sooner compared to light vehicles due to the larger rates of turnover in the fleet [36]. This higher rate of turnover results in newer vehicles that are more likely to be DSRC equipped being purchased. The lower system life of a truck in a fleet comes with drawbacks. Because trucks are not kept in the fleet as long as cars, operational and safety benefits must be able to pay for themselves in a smaller amount of time, and some benefits are not currently able to do so (Deploying Safe Tech.). Respondents to a survey on deploying safety technology and ITS technology into commercial trucks in general agreed that incentive programs would help decrease this payback period [37]. Deployment of connected vehicle technology in commercial vehicles may also differ by vehicle size. In the US, 5% of companies own 66% of the trucks, while 70% of companies have only 1-3 trucks [37]. Any potential incentives may fare better if aimed at larger fleets, who would then sell these vehicles to the smaller fleets down the road when future generations of connected trucks are released [37]. Because of the necessity of short payback periods and other regulations that drive up the cost of buying new trucks, another viable option to increasing the market penetration of connected vehicle technology is finding a way to retrofit the technology into existing trucks [37]. This may also prove beneficial in passenger cars.

On December 13, 2016, the National Highway Traffic Safety Administration (NHTSA) issued a Notice of Proposed Rulemaking (NPRM) that would mandate DSRC capabilities in all new commercial vehicles made after the rule is in place [38]. A phase in period would begin two years after the ruling, and the phase in period would be replaced with mandated standards five years after the ruling [38] [39]. This would standardize the means of V2X communication between all light vehicles in the United States, allowing for greater communication at a faster pace than would occur without the potential rule in place.

The Highway Loss Data Institute (HLDI) projected time it would take for various safety features in vehicles to reach 95% market penetration with and without a hypothetical 2015 mandate [40]. The results, seen below in Figure 8, show the mandate could result in a 95% penetration being reached as much as eight years earlier [40].

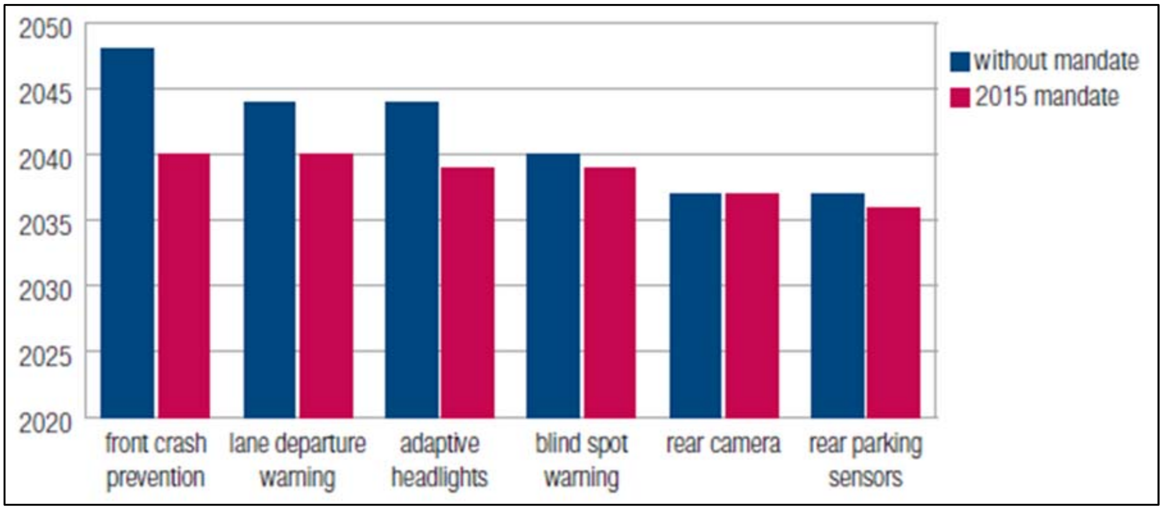

Figure 8: Calendar Year of 95% Market Penetration With and Without a Mandate [40]

2.6.2 The Effects of Market Penetration on V2X Benefits

Market penetration of DSRC equipped vehicles does not have to reach 100% before its benefits can be realized [20]. Determining the extent of connected vehicle benefits at various market penetration rates while projecting the market penetration rate over the next several decades allows agencies to estimate the potential benefits of connected vehicle technology such as reduced emissions and delay at various points in the future. This also allows manufacturers and agencies to determine the payback period for connected vehicle technology, which helps them to better prepare for future deployments [20].

A single BSM can pass between infrastructure and vehicle or between vehicles at a typical range of 300 meters and a maximum range of 1,000 meters [20] [41]. As mentioned in section 2.5.1.4, this range can be boosted by relaying the message via a series of vehicles along a corridor. Increasing this propagation range subsequently increases any potential benefits of connected vehicle technologies, as increased range means increased availability of vehicle and infrastructure information [23]. The ability and the range of this relay depend on the market penetration of DSRC equipped vehicles. With a direct relay of the message, a range of 1000m can be reached with as little as 10% market penetration [41]. This distance was reached under various LOSs, as varying LOSs can result in different densities, affecting a vehicle's ability to find a vehicle within range to relay a message.

Another study tested both the market penetration and the wireless communication coverage of a single message aided by multi-hop propagation. The results can be found below in Table 6 [42]. It found that in peak time the percentage difference in propagation distance between the three market penetration rates decreased with the communication coverage of a single message [42]. As the maximum distance between connected vehicles increases, the likelihood of a connected vehicle finding another connected with whom it can relay the message is more similar between different market penetration rates [42]. Market penetration has a larger effect on total message propagation during the off peak period. Vehicle densities are lower in the off peak period compared to the peak period. This increases the average distance between connected vehicles, meaning the market penetration plays a greater role in the overall propagation distance [42]. These studies show that market penetration has an effect on message propagation, but that sufficient propagation distance can be seen with market penetration as low as 10% [42].

Table 6: Average Distance of Message Propagation (meters) [42]

		Peak time (8-8:30 a.m.)			Non-peak time (6-6:30 a.m.)		
Market penetration rate of equipped vehicles		10 %	20 %	40 %	10 %	20 %	40 %
Wireless communication coverage	100m	90.7	108.4	205.7	30.5	43.5	72.3
	200m	1625.1	**2646.6**	**4054.3**	229.4	429.6	985.6
	500m	**5742.9**	**5783.9**	**5802.5**	**3789.7**	**4901.3**	**5560.6**

Operational and environmental benefits can be realized with only partial market penetration, though as with market penetration, the benefits will not be at their full level [20]. Vehicles on eco-approach could affect the vehicles traveling behind them, resulting in non-connected vehicles optimizing their speed and acceleration. If the paths of connected vehicles are representative of overall traffic at an intersection or corridor, then an adaptive signal control network has the potential to decrease travel times and emissions for non-connected vehicles.

Several studies have investigated the effects of penetration rates on operational and environmental benefits. As discussed previously, Figure 5 and Figure 6 on pages 28 and 28 respectively display fuel savings under various traffic demands and penetration rates [27]. The results indicate that increasing the penetration rate will increase the fuel savings, but as the rate increases, the change in fuel savings decrease [27]. Some of the largest jumps in savings are between 5% and 20% penetration, while the increase in benefits from 80% to 100% are the smallest, with the fuel savings being negative under the highest level of traffic demand [27]. Finally, the results show that fuel savings of 10-15% are feasible with a penetration rate of only 20% [27].

PAMSCOD, mentioned in section **Error! Reference source not found.**, measured the operational benefits of a multi-modal adaptive signal control system that prioritized transit buses over the general vehicle fleet. Figure 9 below looks at three performance metrics, comparing ASC, TSP, and 5 different PAMSCOD penetration rates [30]. Compared to an ASC coordinated system, PAMSCOD shows no reduction in overall vehicle delay until 40% penetration [30]. The increase in throughput coinciding with the increase in the penetration rate does not match that of the study mentioned in Figure 5 and Figure 6, as with PAMSCOD throughput, the rate of increase grows with penetration rate [30]. The benefits at 80% penetration are less than half of that at 100% penetration [30]. The relative benefits in terms of average bus delay are all approximately the same as those of the TSP system, but all levels of PAMSCOD outperform both types of ASC by a minimum of 20% [30]. These studies show that the benefits at partial market penetration can largely depend on the connected vehicle application being tested, and it cannot be assumed the benefits for one application or signal remain the same for others.

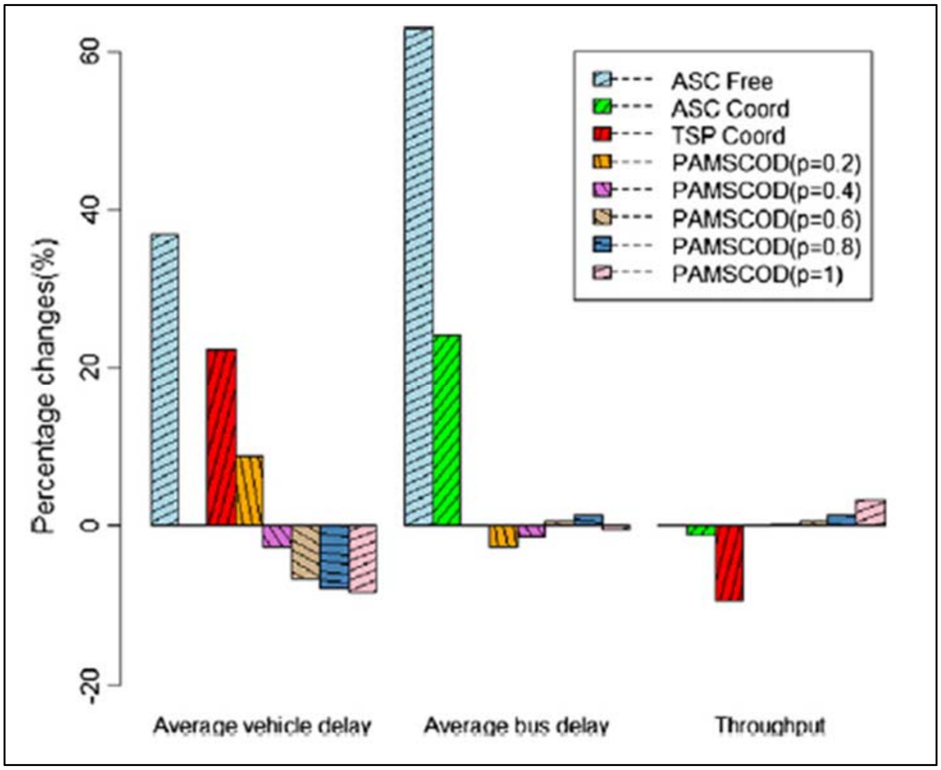

Figure 9: Performance Metrics of PAMSCOD under Varying Penetration Rates [30]

2.7 Probe Data

Probe data has long been used to calculate characteristics of a vehicle fleet by only measuring a small percentage of vehicles. ITS presents an opportunity to capture probe data in a more effective, efficient, and less costly way. With RSUs and OBUs, there is no need to continuously set up or take down data collection equipment [43]. The data can be constantly collected in an electronic format and stored remotely without the need to send anyone to the field [43]. Once agencies are able to get past the high implementation cost of connected vehicle technology, the cost of data collection is self is very low, especially when looking at the unit price per unit data [43].

Increasing radiofrequency demand has the potential to put a strain on DSRC's ability to carry all vehicular messages effectively. As the number of connected vehicles rises, the sheer volume of data being collected had the potential to become too overwhelming [20]. Sampling the overall data using probe data has the potential to cut down on the message and data volume while still providing an overall representative snapshot of the entire fleet.

As the number of connected vehicles rises, there are concerns over the volume of data and radio traffic DSRC will use [20]. As demand increases in other areas, it has already been suggested by some that the 5.9 GHz band spectrum currently reserved for DSRC-based ITS applications be opened up for other uses [20]. There is also the concern over the lack of state and local resources to maintain V2I systems [20]. There may reach a point where a state or local agency is unable to process or store the data collected by RSUs. Using probe data would help the problem of message congestion by drastically lowering the number of messages passed and the amount of data processed and stored. If a V2I application can realize virtually full benefits at less than full penetration rate, the RSU does not have to pass messages to every connected vehicle in the network. This has the added effect of lowering the amount of data received and stored in the local or state agency's TMC.

A paramount issue with probe data is determining the minimum sample size of the probe needed to gather data that reflects the conditions of the overall fleet. This in turn determines the minimum DSRC equipped vehicle market penetration needed to gather data that represents the overall fleet. Zou et. al. studied various probe data penetration rates to determine the average error percentage [44]. The results can be found below in Table 7

[44]. The results are intuitive, with the average error percentage dropping as the probe penetration rate increases [44]. It is also worth noting that the drop in average error percentage decreases as the probe penetration rate increases from 5% to 10% compared to that of it increasing from 1% to 5%. Future studies that include larger probe penetration rates would be helpful in determining how this pattern continues [45]. In a similar study, Rehborn et al found that a probe penetration of only two percent would deem what was considered to be premium quality data [45]. This facilitates the analysis, aggregation, and sharing of vehicular data within and between state, local, and federal agencies to better measure [45].

Table 7: Average Error Percentage for Various Probe Penetration Rates [44]

Probe Penetration Rate	1%	5%	10%
Avg. Error Percentage	27.6%	12.5%	8.2%

CHAPTER 3. METHODOLOGY

The methodology of this experiment begins with the building of the corridor and the vehicle record file in VISSIM 9.00. In order to make this experiment repeatable, the methodology will mainly include any deviation taken from the VISSIM default features and settings. This is to allow for a potential repeat of the experiment without the inclusion of redundant steps in the model building process. Once the model has been run under all the desired conditions, the vehicle record files are then converted to a replica of the BSM. While not critical to the experiments in this thesis this step relates to the overall project, as it makes it possible to test the benefits or overall measurement accuracy of the BSM without having to set up the communications network. With the data converted to BSM format, it can then be plugged into the MOVES-Matrix. Although the raw vehicle record files from this report could be plugged directly in to the MOVES-Matrix, the conversion to a BSM allows for laying the foundation for future efforts. The MOVES-Matrix results can then give the percent error of the sample for all or part of the roadway network.

3.1 VISSIM Model Building

For the most part, VISSIM's default settings and values were kept. This is due to the scope of the model. As the main purpose was to explore data sampling, it was not necessary to manipulate the model in such a way that precisely replicated the real world conditions of that part of North Avenue, including the modeling of the dozens of side streets and driveways that line the corridor.

3.1.1 Data Sources

Three vehicle types were chosen for the model. The default settings for passenger cars were retained, but changes were made to the default heavy vehicle fleet. The default 33.5 ft EU-04 Heavy Grade Vehicle (HGV) was not selected for use in the model. Selected in its place were the 28.9 ft EU-05 and the 55 ft WB-50 HGVs. These vehicles were selected to better represent the class 5 single unit trucks and class 8 tractor trailers present on North Avenue. The components of these vehicle types can be found below in Table 8 and Table 9. For the WB-50, multiple components were needed in order to create a vehicle with both a tractor unit and a trailer.

Table 8: Vehicle Components for the WB-50 Tractor Trailer

Count: 2	Index	File3D	Length	Width	ShaftLen	JointFront	AxleFront	AxleRear	JointRear
1	1	HGV - US AASHTO WB-50 Tractor.v3d	21.635	9.603	0.000	0.000	5.112	16.869	17.101
2	2	HGV - US AASHTO WB-50 Trailer.v3d	41.594	8.660	0.000	3.695	3.699	33.863	40.952

Table 9: Vehicle Components for the EU-05 Single Unit Truck

Count: 1	Index	File3D	Length	Width	ShaftLen	JointFront	AxleFront	AxleRear	JointRear
1	1	HGV - EU 05 Tractor.v3d	28.881	8.189	0.000	0.000	5.115	18.681	28.292

The power functions were edited for the trucks to better represent the standard horsepower of class 5 and class 8 trucks. These distributions are uniform, meaning there is a constant probability of selecting a desired power or weight for any value between the lower bound and upper bound figures. In order to minimize variability within vehicle fleets of the same composition, all trucks of the same class were given the same power distribution. Within VISSIM, power distributions are not allowed to have the same lower bound and upper bound figures, meaning the upper bound figure in Table 10 below was set to the minimum difference of 0.01 kW above that of the lower bound. Both distributions are in metric units, as that is the only option for such distributions in VISSIM.

Table 10: Power Distributions Created for Single Unit Trucks and Tractor Trailers (kW)

Coun	No	Name	LowerBound	UpperBound
1	1	Single Unit Truck	150.00	150.01
2	2	Tractor Trailer	300.00	300.01

Additionally, the weight distributions for each truck type was changed from the default, as the default truck distribution for VISSIM was assigned to all truck types. As with the power distributions, the weight distributions were uniform, with the upper and lower bound values set to the upper and lower limits for class 5 and class 8 trucks. These values can be seen below in Table 11. As with the power distributions, these values were converted to metric, as it is the only unit system for weight distributions in VISSIM.

Table 11: Weight Distributions Created for Single Unit Trucks and Tractor Trailers (Kg)

Coun	No	Name	LowerBound	UpperBound
1	9	Class 5 SU	7258.00	8845.00
2	10	Class 8 Tractor Trailer	14959.00	36287.00

Where data were not known, engineering judgement was used to fill in the gaps. Detector data were not given for two of the 19intersections. As these intersections could no longer run as actuated signals, all phases were set to remain at the maximum length. Additionally, the vehicular speed distributions needed for this model were not found in the list of default distributions. Speed distributions were adjusted using speed data from both driving through the corridor and observing other cars through the corridor. Reduced speed distributions were also created for turning movements and lane changes to a left or right turning bay. In all, five new speed distributions were created: a lane change distribution, left turn, and right turn distribution for all vehicles as well as general speed distributions for passenger cars and for heavy vehicles. For these distributions, both types of trucks were attached to the same distribution. The reduced speed distributions for turning and changing lanes were important for gathering realistic energy data, as deceleration and acceleration before and after turning movements have the potential to significantly affect the energy used by vehicles. The upper and lower bounds for all of these uniform distributions can be found below in Table 12.

Table 12: Speed Distributions created for the VISSIM Model

Coun	No	Name	LowerBound	UpperBound
1	1	low radius right turns	8.00	12.00
2	2	high radius right turn	12.00	15.00
3	3	left turns	15.00	20.00
4	4	Lane Change to Turn Only Lane	14.00	16.00
5	5	35 mph cars North Ave	32.00	38.00
6	6	35 mph truck North Ave	30.00	36.00

3.1.2 Corridor Segmentation

In order to better study smaller parts of North Avenue, each street in the network was split into small segments of approximately 200 linear feet. As no distance between two intersections was an exact multiple of 200 ft, the length of the middle segment was set to make the correct segment length. If the distance between two intersections was under 400 ft, then two segments of equal length were created. For example, the distance between the intersections of Juniper Street and Piedmont Avenue was only 376 ft, so two segments of 188 ft were created. When under these guidelines, the middle segment between intersections would end up with a length under 125 ft, the middle segment is absorbed into the adjacent segments. By keeping the segments as close to 200 ft as possible, segments can be better compared with each other. These segments were measured from the edge of the intersections as opposed to their central points. The intersections themselves became their own rectangular segments, with dimensions as unique as each intersection. The segment boundaries are not part of the VISSIM model, and these segments are only used in post-processing the VISSIM output data. By segmenting the corridor, data analysis can more easily be completed at smaller scales. Figure 10 below shows the basics of the segment nomenclature. Each intersection is given a number divisible by ten, with the number increasing by ten as one moves from west to east. As one moves west to east away from the intersection, each segment is given the intersection number with a hyphen and increasing numbers starting from one. Moving from intersection 110 Figure 10, the segment numbers start at 110-1 and increase to 110-3 before ending at the subsequent intersection. For side streets, a similar nomenclature is given, but the segment numbers for each direction do not increase as one moves in the same cardinal direction such as south to north. Instead, both directions see the segment number increase as one moves away from the intersection. Each segment is assigned points at the beginning, middle, and end of the segment. The tables of segment IDs and their corresponding cross streets can be found in Appendix B.

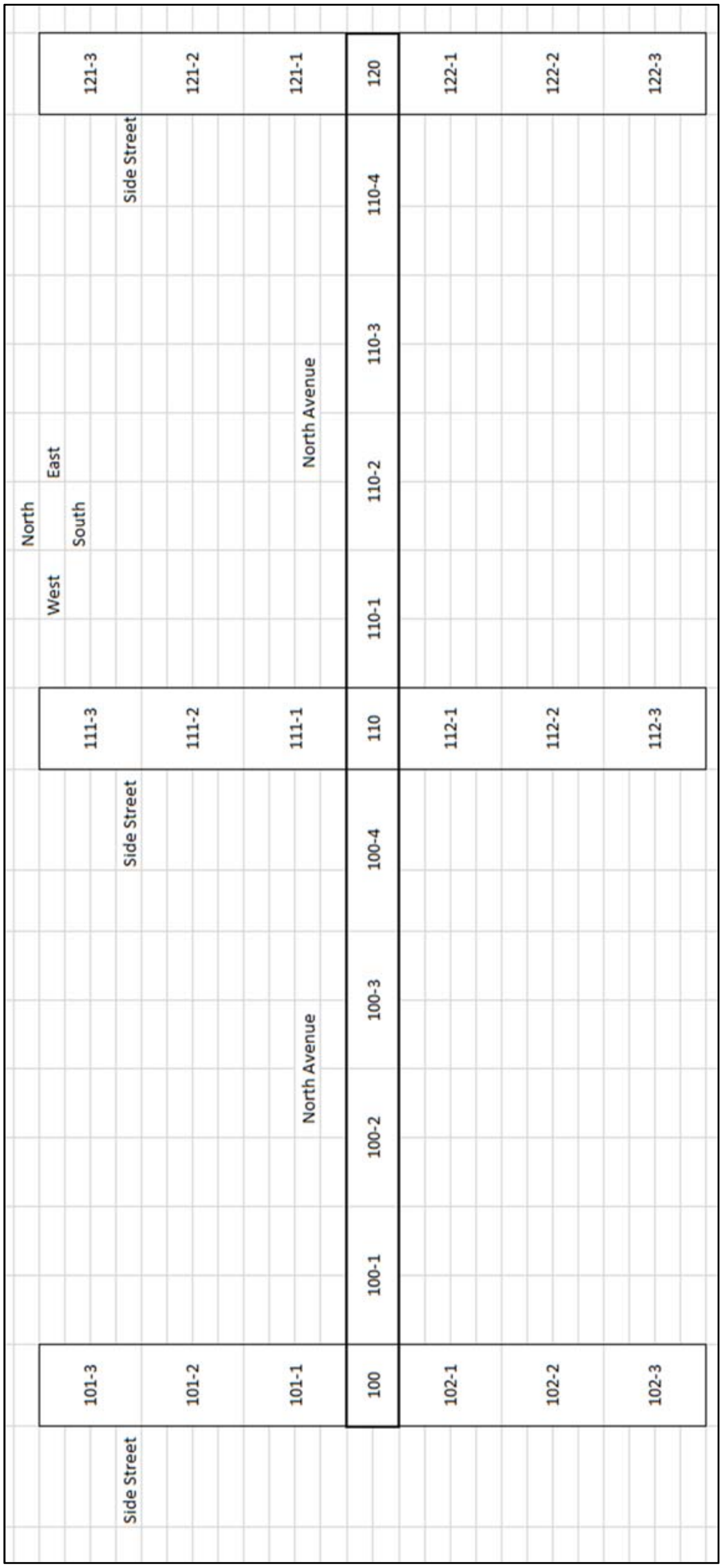

Figure 10: Corridor Segment Nomenclature

3.1.3 Corridor Grade

Roadway grade affects the outputs of the MOVES-Matrix in two ways. Within VISSIM, changing the grade of the road affects the acceleration distributions of vehicles, and can begin to affect a vehicles' ability to reach its desired speed [3]. Within the MOVES-Matrix, grade is a factor used in calculating VSP. For this model, roadway grade for North Avenue and the side streets was obtained, and the average grade for each corridor segment created in the previous section and intersection was calculated by dividing the change in the z coordinate from the beginning to the end of the segment by the overall length of the segment. Once this was completed, the grades were rounded to the nearest whole percent. An example of this can be seen below in Table 13. These segments, which cover Centennial Olympic Parkway south of North Avenue, each have an average grade that was calculated to a small fraction of a percent. The adjusted grades help smooth out the corridor and allow for streamlining the process of adding the grade by allowing for consecutive segments to have the same grade.

Table 13: Raw and Adjusted Segment Grade for Centennial Olympic Parkway Drive

Segment ID	Mean Grade (%)	Adjusted Grade (%)
82-1	-5.080184	-0.05
82-2	-2.7638425	-0.03
82-3	-0.4749434	0

From there, z-offsets were calculated, which found the z-coordinate for the beginning and end of each segment relative to the lowest point on the corridor. These z-coordinates were inserted into the model by adding in spline points along VISSIM links and setting them to the elevation needed. These z-coordinates are what VISSIM can use to calculate grade and determine how that affects vehicular speed and acceleration, and when viewed in 3D mode can allow users to view grade changes. Figure 11 below shows the model at a point with some of the largest grade changes. Looking northeast, North Avenue runs left to right and Boulevard run away from the screen on the left hand side. The hill seen on North Avenue reaches 10% in grade at points, and slopes down to Glen Iris Drive and Ponce City Market.

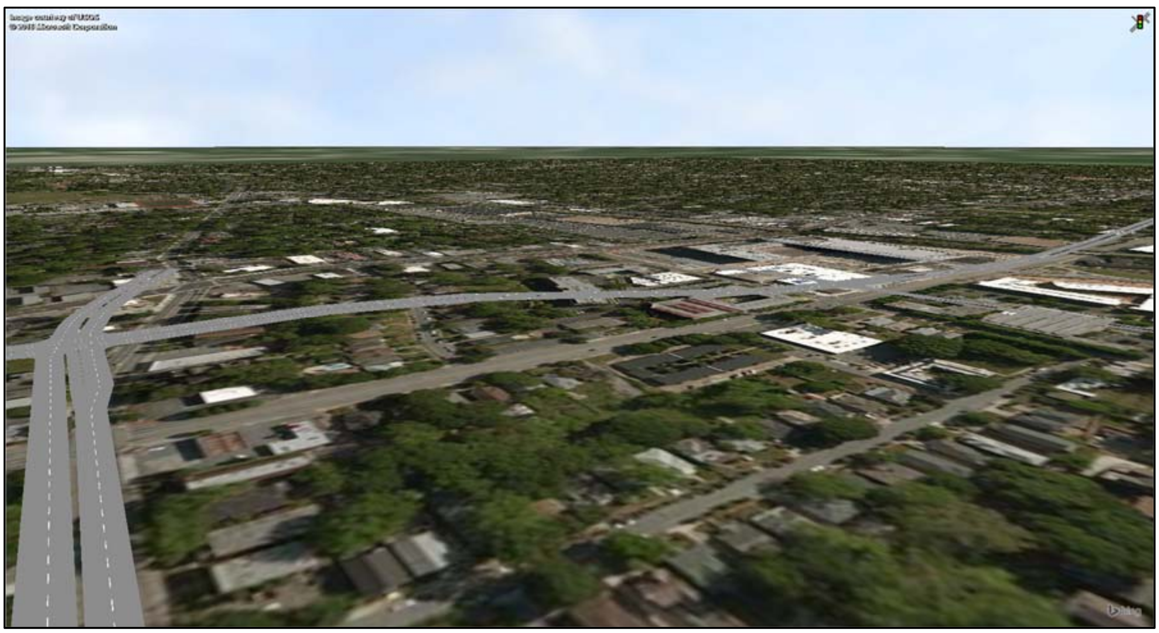

Figure 11: North Avenue Corridor with Grade Inserted

3.1.4 Model Calibration

Although the model was not designed to perfectly replicate the field conditions of North Avenue, some calibration was required in order to make traffic volumes and vehicular behavior realistic. The traffic volumes provided by the City of Atlanta did not completely match up from intersection to intersection. This is due to the minor differences in day-to-day traffic as well as local sources and sinks. When the cumulative volumetric difference in traffic leaving an intersection and arriving at the next intersection remained under 5%, the difference was considered negligible. For these intersections, the route decisions were adjusted so that the discrepancy was entirely in the through traffic, as opposed to being split between the through, left turning, and right turning movements. When the difference was 5% or greater, a source or sink was created to increase or decrease the traffic flow in order to balance the traffic volumes. This was done by considering the cumulative effects of traffic discrepancies, as consecutive intersections with small traffic differences have the potential to result in an unacceptably large discrepancy.

When route decisions were originally placed in VISSIM, subsequent model runs showed an unrealistic amount of queueing and delays due to vehicles changing lanes very close to intersections. This does not reflect observed traffic conditions. Without origin-destination (OD) travel data, changes were made to the car following model and links in order to maximize the distance between route decision points and the subsequent intersections. Within the Wiedemann 74 car following model, the "Advanced Merging" option was selected. This results in a higher percentage of cars changing lanes sooner after crossing over a route decision point [3]. Within the Wiedemann 74 car following model and the Vehicle Route Decisions menu, the "Consider subsequent static routing decisions" and "Combine static routing decisions" options respectively were selected. These options allow vehicles to look ahead to future routing decisions on the same link as the vehicle, resulting in vehicles that know their routing decision more than an intersection in advance. To help these systems work better, single links were used for multiple intersections wherever the roadway geometry allowed, and new links were only created where the number of lanes changed. If after all of these changes, the decision points could not be pulled back further, then the routing decisions of multiple intersections would be combined.

When all inputs had been calibrated, the model was run under various conditions to ensure it would stay at equilibrium for an hour-long simulation. Equilibrium was determined by analysing the number of vehicles in the network as well as the vehicular travel times of several dozen segments within the corridor. The number of vehicles in the network should increase over the first several minutes as the network fills with vehicles and then resemble a sine wave with periodic but constant increases and decreases in traffic. If the number of vehicles is always increasing, it means the model is unable to process the number of vehicles entering the corridor and not in equilibrium. The model was run under the most severe traffic conditions expected to be tested to determine if any part of the model was unable to process the volumes inputted. **12** below shows the number of vehicles in the network every sixth second during a 75-minute simulation run. Seventy-five minutes allows 15 minutes for the model to reach maximum capacity and 60 minutes to run at maximum capacity. Even though the number of vehicles increases from 1500 to 2100 seconds, the number falls after, and the number of vehicles stays within the same range.

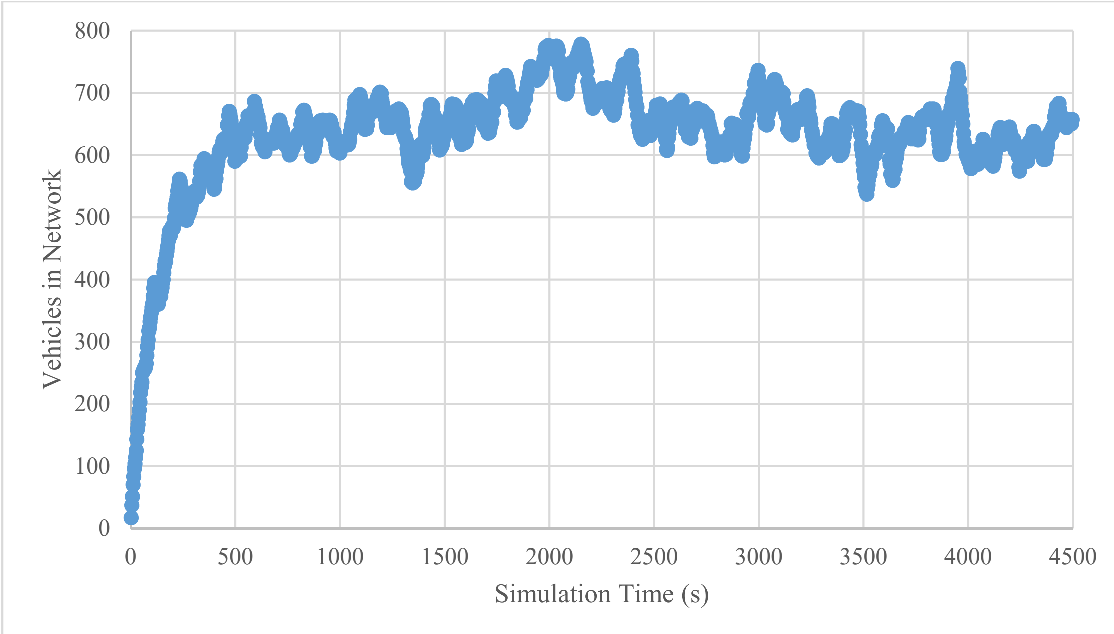

Figure 12: Vehicles in the Network during a Calibration Run

3.1.5 Fleet Compositions

The fleet composition was determined by two factors: ratio of single unit class 5 trucks to class 8 tractor trailers, and the overall percentage of trucks. The ratio of class 5 to class 8 trucks was set to be 3:1. This ratio was selected based on the judgement of the research team. This ratio was kept the same for every trial, eliminating the change in the ratio from being a confounding variable in interpreting the simulation results.

In all, seven different fleet compositions were chosen to be tested. The list of fleet compositions and breakdown of vehicle compositions can be found below in Table 14. Different fleet compositions were chosen for various reasons. A baseline of 0% trucks was chosen in order to understand how energy usage change when moving from a fleet without trucks to a fleet with trucks. As this fleet contains no trucks, it cannot be used as a baseline when looking at changes in single unit trucks and tractor trailers energy usage. Therefore, the baseline for these vehicle types is considered to be a vehicle fleet with 1% overall trucks. Percentages of 1, 2, 5, and 10 were chosen to cover the reasonable range of potential truck percentages along the North Avenue corridor. Situated near multiple railyards with the dual designation of city-designated truck route and state-designated strategic truck route, a vehicle fleet with as high as 10% trucks can be expected [47] [48]. While 20% and 50% truck rates are likely unrealistic for the North Avenue they were included to understand the potential impacts under more extreme conditions.

Table 14: Vehicle Compositions

Overall Truck Percentage (%)	Passenger Car Percentage (%)	Class 5 Truck Percentage (%)	Class 8 Truck Percentage (%)
0	100	0	0
1	99	0.75	0.25
2	98	1.5	0.5
5	95	3.75	1.25
10	90	7.5	2.5
20	80	15	5
50	50	37.5	12.5

3.2 Running the Model

The North Avenue VISSIM model was run ten times at each overall fleet composition for a total of 70 runs. Each run was given its own random seed, which slight changes to both the number of vehicles in the model and the order in which they arrive. These slight variations add stochasticity, and must be tested in order to obtain more accurate results. Without multiple runs at the same conditions, only that particular run and not the overall model have been tested.

Each model run was simulated for 4500 seconds, with data collection starting at 900.1 seconds. This allows the model 15 simulation minutes to reach equilibrium, which was shown in **Error! Reference source not found.** to be sufficient time. The Vehicle Record files were set to collect data every time step, which for this model was the default 0.1 seconds. The data that Vehicle Record files collect is selected by the user from a list of attributes, and can be selected for the entire fleet or for specific vehicle types. For this experiment, data was collected for every vehicle. **Figure 13** below shows an example of the introduction to a Vehicle Record file, which includes the attributes selected and their units.

```
$VISION
* File: C:\Users\jbolen7\Desktop\North Ave Model Sept 13 v2\North Ave Corridor PM.inpx
* Comment:
* Date: 10/2/2017 8:50:36 AM
* PTV Vissim: 9.00 [06]
*
* Table: Vehicles In Network
*
* SIMSEC: SimSec, Simulation second (Simulation time [s]) [s]
* STARTTM: StartTm, Start time (Network entry time [simulation second]) [s]
* NO: No, Number (Number of the vehicle)
* COORDFRONT: CoordFront, Coordinate front (Coordinate of front end of vehicle at the end of the time step)
* COORDREAR: CoordRear, Coordinate rear (Coordinate of rear end position of vehicle at the end of the time step)
* SPEED: Speed, Speed (Speed at the end of the time step) [mph]
* ACCELERATION: Acceleration, Acceleration (Acceleration during the time step) [ft/s2]
* VEHTYPE: VehType, Vehicle type (Select Vehicle type from the list box)
* WIDTH: Width, Width (Vehicle width, depending on 2D/3D model distribution (see "Using 2D/3D model distributions"). The width is relevant for
overtaking within the lane (see "Applications and driving behavior parameters of lane changing")) [ft]
* LENGTH: Length, Length (Minimum and maximum vehicle length (see “Using 2D/3D model distributions”)) [ft]
* LANE\LINK: Lane\Link, Lane\Link (Number of the link or connector, in which the lane is located)
*
* SimSec; StartTm; No; CoordFront; CoordRear; Speed; Acceleration; VehType; Width; Length; Lane\Link
*
```

Figure 13: Example Vehicle Record File Introduction

3.3 Data Processing

Taking data from its raw format in a VISSIM Vehicle Record File to a final list of energy rates takes several steps of processing, each one assisted by python scripting. Each vehicle’s data for each second must be condensed from 10 hertz (Hz) to 1 Hz, assigned to the proper location within the corridor, and analyzed to determine its energy consumption outputs.

An important consideration when consolidating data and converting its different elements is that this process was to be able to be replicated if given a BSM. At every step in the data processing, all data elements taken from VISSIM or calculated in further steps would be found in or can be calculated from a BSM. At no point in this experiment is a replica BSM actually created, as to do so would be redundant in this case. Instead, the data processing steps have been designed in such a way that minor alterations in scripting is all that is needed to shift from processing a VISSIM Vehicle Record File to processing a BSM.

3.3.1 Data Condensing

The BSM is broadcasted from vehicles at a 10 Hz rate. This fast rate is intentional, as such a low latency is critical for safety applications in which one-tenth of a second can be the difference between being in and avoiding a collision. This low latency is not required and cannot be used with the MOVES-Matrix, as it has been designed for 1 Hz data. As the MOVES-Matrix process involves significant binning, the increased precision of 10 Hz data is rendered useless. Because of this, the 10 Hz data must be condensed into 1 Hz data.

Each full second of data is originally made up of 10 data points. The speed and acceleration for the entire second are found by using the median of the ten points for each value and applying it to the entire second. The position for the second is found by taking the median position of the original ten data points and subsequently converting it from VISSIM's (X, Y) coordinate system to latitude and longitude. Two factors calculated in this step are the vehicle's grade and bearing. The grade is calculated by dividing the change in the z-axis by the change in distance travelled in the XY plane. The bearing is calculated by analysing the coordinates at the front and rear of the vehicle. Bearing is not needed to calculate the energy usage, but instead allows vehicles to be separated by their direction of travel, i.e. differentiating between a northbound vehicle and a southbound vehicle. The scripting for this step can be found in

. Graduate student Somdut Roy, under the guidance of Haobing Liu and Dr. Angshuman Guin, is credited with the development these scripts. Also in the appendix is the scripting that would be needed to turn a BSM into the same condensed data file. Subsequent intermediate steps no longer require the direct use of a BSM or Vehicle Record file. Figure 14 below show an example of the introduction to the condensed file, showing the attributes kept from the vehicle record file and their units.

```
* SEC: Lower Bin of Simulation second [s]
* VEHNR: Vehicle Number
* VEHTYPE: Vehicle Type (PC/ B/ SU/ TT)
* LAT: Median Latitude
* LONG: Median Longitude
* SPEED: Average Speed [mph]
* ACCL: Average Acceleration [mph/s]
* FRAC: Fraction of 1 second bin used
* GRADE: Representative gradient (fraction) of the second bin
* BEARING: Bearing of the vehicle (in degrees)

* SEC;VEHNR;VEHTYPE;LAT;LONG;SPEED;ACCL;FRAC;GRADE;BEARING;
```

Figure 14: Example Condensed Data File Introduction

3.3.2 Segment Association

Once the data have been condensed, each line of vehicular data is sorted into the roadway segments detailed earlier in this chapter. By sorting the data, analysis can take place at smaller levels than merely looking at the entire corridor. It allows researchers to screen out the side streets or look at parts of the roadway close to or further from the intersection. For this effort, each segment along North Avenue itself has been grouped into one of three overall pieces. North Avenue is a diverse corridor, and the three pieces, detailed below in Table 15, split the corridor up into similar types, allowing for analysis to take place that pinpoints the industrial, high density, and residential aspects of it. Figure 15 below shows an example of an introduction to the segment association file, showing the attributes and their units.

```
* SEC: Lower Bin of Simulation second [s]
* VEHNO: Vehicle Number
* VEHTYPE: Vehicle Type (PC/ B/ SU/ TT)
* SEGID: Segment ID
* ENERGY: Energy [kJ]
***EMISSIONS***
* EMISSIONS_CO2: Carbon dioxide [gm]
* EMISSIONS_HC: Hydrocarbon [gm]
* EMISSIONS_CO: Carbon Monoxide [gm]
* EMISSIONS_NOX: Oxides of Nitrogen [gm]
* EMISSIONS_VOC: Volatile Organic Compounds [gm]
* EMISSIONS_PM10: Particulate Matters <10 microns [gm]
* EMISSIONS_PM2.5: Particulate Matters <2.5 microns [gm]

* SPEED: Average Speed [mph]
* ACCL: Average Acceleration [mph/s]
* VSP: Vehicle Specific Power [m^2/s^3]
* FLOWDIR:  'WE' or 'EW' or 'NS' or 'SN'

*
SEC;VEHNO;VEHTYPE;SEGID;ENERGY;EMISSIONS_CO2;EMISSIONS_HC;EMISSIONS_CO;EMISSIONS_NOX;EMISSIONS_VOC;EMISSIONS_PM10;EMISSIONS_PM2.5;SPEED;ACCL;VSP;FLOWD
IR;
```

Figure 15: Segment Association File Example Introduction

Table 15: Boundaries of the Three Overall Corridor Pieces

Segment Number	Western Terminus	Eastern Terminus
1	Northside Drive	I-75/I-85 Ramp
2	I-75/I-85 Ramp	Juniper Street
3	Juniper Street	Freedom Parkway.

3.3.3 Energy Analysis

Once sorted, the data were run through the MOVES-Matrix and placed into output .csv files. Each run has a series of .csv files that separates the data based on factors such as direction of travel, vehicle type, and metrics such as total, average, or standard deviation of the energy usage. For both the average per-vehicle energy and standard deviation of the energy at each segment, an output file is created for each vehicle type as well as the entire fleet for westbound and eastbound traffic on North Avenue as well as the entire network.

Additional output files are created calculating total energy for westbound and eastbound traffic on North Avenue as well as the whole network. The segment lengths are included, but the data are not normalized to a standard 200 ft segment length. Table 16 below is an example of a final output file, showing the energy and emissions values for every segment. Although this experiment analyzes only energy data, the inclusion of emissions data in the scripting allows future research to more readily include the analysis of energy data. The first column on the left is the start time of the time period being analyzed. This is irrelevant for this experiment as the data is being analyzed for the entire hour, but allows future researchers to analyze data in various time increments.

Table 16: Example Energy Output File

Time[s]	SegmentID	Latitude	Longitude	#vehicles	Energy[kJ]	CO2[gm]	HC[gm]	CO[gm]	NOX[gm]	VOC[gm]	PM10[gm]	PM2.5[gm]	Speed[mph]	Accel[mph/s]	VSP[m^2/s^3]
0	20-1	33.76997	-84.40587	431	337.75065	24.35911	0.00132	0.226316	0.005685	0.000679	0.000582	0.0005162	30.81682382	1.639630367	12.00076722
0	20-2	33.76997	-84.40518	435	434.22685	31.34429	0.00097	0.04875	0.005053	0.000547	0.000351	0.0003131	5.510896474	-0.408822674	-0.96614309
0	31-1	33.77073	-84.40523	1281	199.05321	14.35909	0.00042	0.040961	0.002146	0.000229	0.000163	0.000145	19.84227035	-0.30472976	0.927466707
0	31-2	33.77105	-84.40576	1281	137.99295	9.958661	0.00023	0.015753	0.001329	0.00013	8.44E-05	7.52E-05	34.16278651	-0.119933163	3.002498025
0	31-3	33.77136	-84.4063	1281	195.99038	14.14174	0.00051	0.060208	0.002537	0.000271	0.000204	0.0001811	33.95740833	0.489180691	6.827890072
0	32-1	33.76958	-84.4047	572	356.95504	25.78352	0.00104	0.107998	0.005292	0.000565	0.000427	0.0003794	9.779413458	-0.381352821	-0.595770259
0	32-2	33.76904	-84.40476	572	146.94901	10.59759	0.00025	0.018804	0.001322	0.000137	9.33E-05	8.31E-05	34.36605631	-0.040962462	2.697309089
0	32-3	33.76849	-84.4048	572	217.3755	15.66065	0.00081	0.137806	0.003046	0.000417	0.000341	0.0003025	33.926474	0.680864	6.65902949
0	30-1	33.77001	-84.40351	1317	221.00305	15.93817	0.00048	0.046094	0.002382	0.000259	0.000194	0.0001727	15.30377602	-0.401253105	-0.163129749
0	30-2	33.77002	-84.40285	1312	141.4086	10.19799	0.00027	0.024061	0.001389	0.000149	0.000103	9.17E-05	32.62873761	-0.150244216	2.551638135

CHAPTER 4. RESULTS

Included in the output files created through the data processing process are energy and seven types of GHGs, CO_2, hydrocarbons (HC), carbon monoxide (CO), nitrous oxides (NO_x), Volatile Organic Compounds (VOC), and Particulate Matter at both the 10 micron (PM_{10}) and 2.5 micron ($PM_{2.5}$) levels. For this experiment, only the energy levels will be analyzed. The standard metric being examined is the average amount of energy needed for a vehicle to travel the entire length of the North Avenue corridor. As previously mentioned, ten runs at different random seed values were executed at each fleet composition. The mean value of each is used in the results below. To measure the variability and determine if results are statistically significant, 95% Confidence Intervals (CI) have been included as error bars in all graphs. These metrics will be analyzed for the entire fleet as well as separated by each of the three vehicle types. The traffic in the eastbound and westbound directions will be analyzed separately before being averaged. The two travel directions have significantly different traffic volumes, and separating the data by direction of flow may give some insight as to how varying traffic volumes alongside variations in truck percentage affects energy usage.

4.1 Westbound Energy

Overall, the westbound direction has lower vehicle counts than the eastbound direction. As lower vehicle counts typically correspond with lower amounts of queueing and spillback, the westbound direction is hypothesized to generally have the lower energy usage. Tables displaying the numerical values of the figures in this section can be found in **Error! Reference source not found.**.

The overall results for average energy needed to travel the length of the North Avenue Corridor westbound can be found below in Figure 16. As expected, the energy usage of passenger cars is much lower than that of single unit trucks, which is in turn lower than tractor trailers. As the vehicle composition shifts towards more trucks and fewer passenger cars, the average per-vehicle energy of the entire fleet shifts closer to that of single unit trucks. With all four vehicle types together on one graph, their shifts in variability can also be directly compared. At 1% trucks, only 0.25% of all vehicles on the corridor are tractor trailers. The variability in both truck types can be seen decreasing as the number of vehicles of those types increases. This leads to a slow increase in the overall fleet variability.

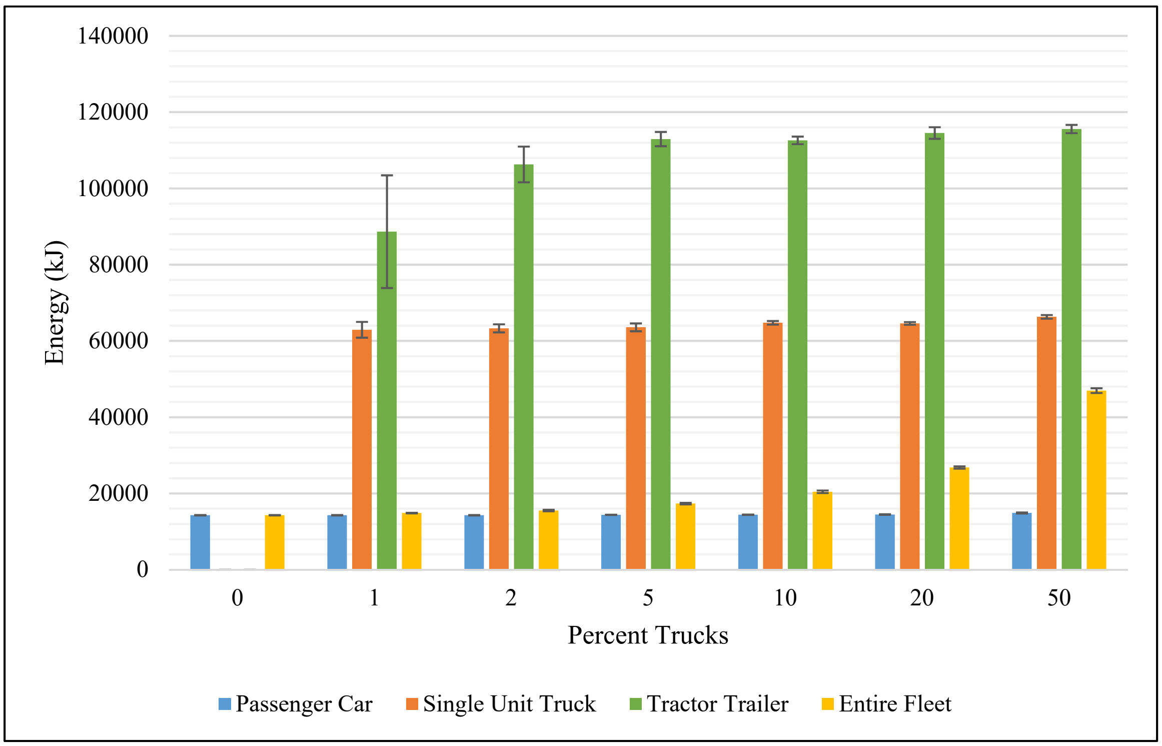

Figure 16: Average Energy on the North Avenue Corridor for Westbound Vehicles

The average energy on the corridor for a westbound passenger car can be seen below in Figure 17. The change in average energy is small, and it is not until the fleet is 5% truck that there is a statistical significance with the baseline, with an increase in average energy of 0.70%. At 20% and 50% trucks, the energy values increase at a higher rate, with increases of 1.30% and 4.01% respectively. The variability of results is relatively small, with the largest CI of ±129.71 kJ occurring at 50% trucks. Unlike other instances, the variability does not uniformly increase alongside truck percentage. Instead, at ±33.62 kJ, the lowest CI occurs at 5% trucks. Additionally, the CIs at 0%, 1%, and 2% trucks are all higher than that of 10%. At 1% and 2% trucks, the average per-vehicle energy rate is less than the baseline by 0.10% and 0.04% respectively. These decreases are well within the 95% confidence intervals of all three truck levels, and as such there is no statistical difference between the three.

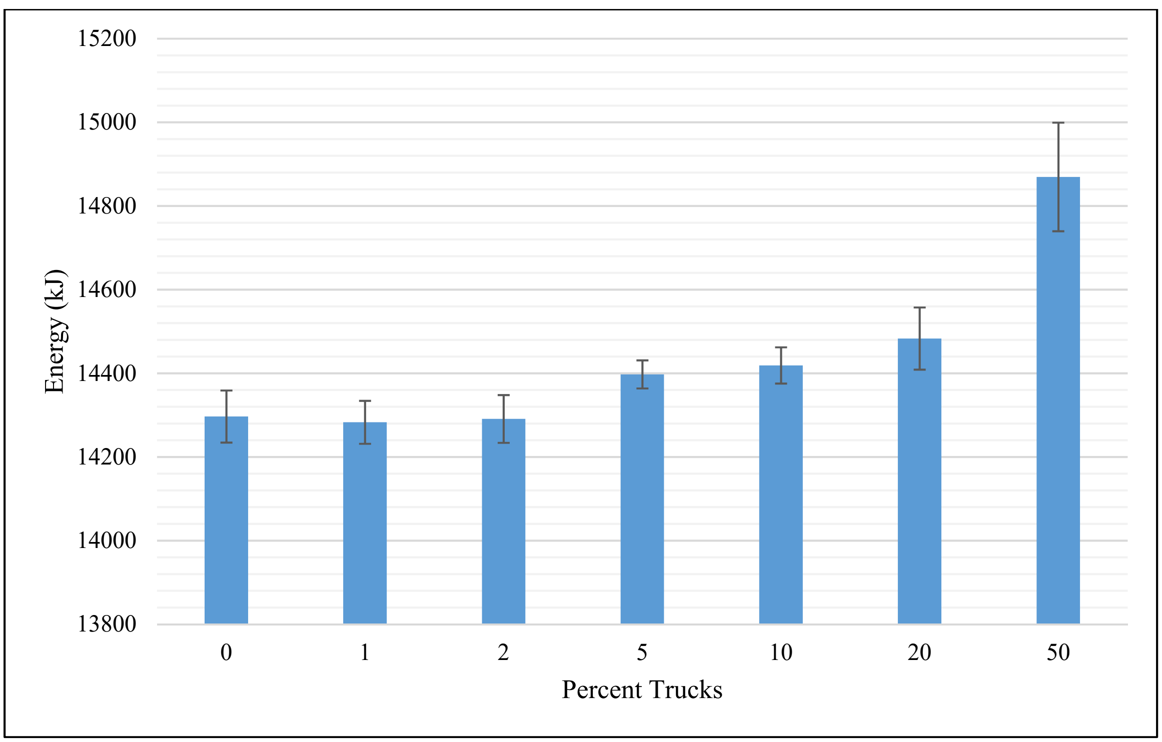

Figure 17: Average Energy for a Westbound Passenger Car

The average energy for a westbound single unit truck can be found below in Figure 18. Here, per-vehicle energy increases at a faster rate compared to that of passenger vehicles. For comparison, at 5% trucks, the per-vehicle energy increase for single unit trucks increases by 1.02% compared to its baseline of 1% trucks. This changes to increases of 2.89% and 5.39% at 10% and 50% trucks respectively. Despite the larger changes from the baseline, the single unit truck data has much higher variability, with a CI at the baseline of ±2069.92 kJ. This increase in variability means that there is no statistical significance from the baseline until the fleet reaches 50% trucks. As with westbound passenger cars, there is a decrease in energy when moving from a lower truck percentage to a higher truck percentage. Compared to the aforementioned increase at 10% trucks, the increase from the baseline at 20% trucks is only 2.66%. This increase is within the two values' CIs, meaning that the general increase in energy is still intact.

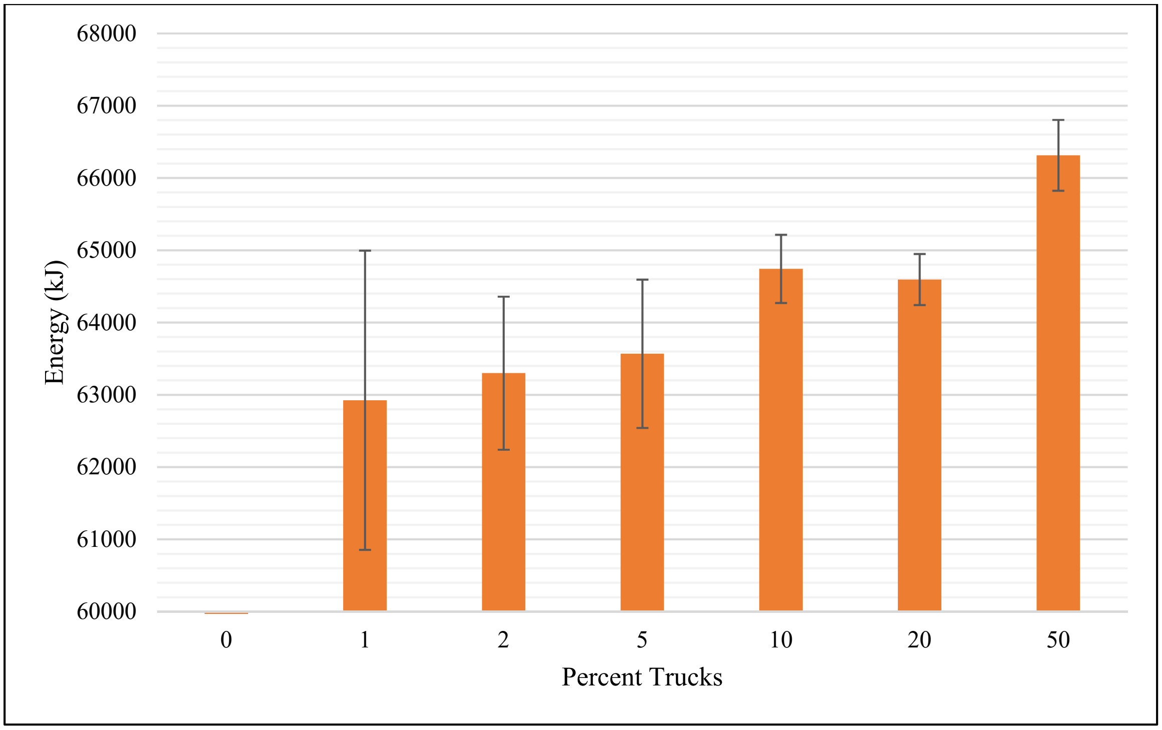

Figure 18: Average Energy for a Westbound Single Unit Truck

The average energy for a westbound tractor trailer can be found below in Figure 19. This group has the largest increase from the baseline and variability of all vehicle types in both the westbound and eastbound directions. At 19.89%, the increase in average energy from 1% to 2% trucks is the largest increase from the baseline to the truck percentage immediately above the baseline. Despite this large increase, there is no statistical significance between the two at a 95% confidence level. The overall pattern of increases for tractor trailers is also different than that of other vehicles or the fleet wide aggregate. While most changes in energy between consecutive fleet compositions increase alongside the increase in truck percentage, tractor trailer energy sees its largest change in energy come from its smallest change in truck percentage. This is due to the large variabilities at 1% and 2% trucks of ±14776.9 kJ and 4682.75 kJ respectively. At 1% trucks, only 0.25% of vehicles in the fleet are tractor trailers, leading to very large variations from run to run. For all ten runs at 1% trucks, there were multiple roadway segments over which no tractor trailers drove. With so few tractor trailers, differences in the total delay and number of stops each tractor trailer underwent played a much larger role compared to that of passenger cars. As previously mentioned, the variability for single unit trucks can also dwarf that of passenger cars, but with three single unit trucks for every tractor trailer, the latter experienced much higher delay compared to the former. As seen below in Figure 19, the average per-vehicle energy at 1% trucks was 88468 kJ, but the average energy for individual runs varied from 43,325 kJ to 112,200 kJ.

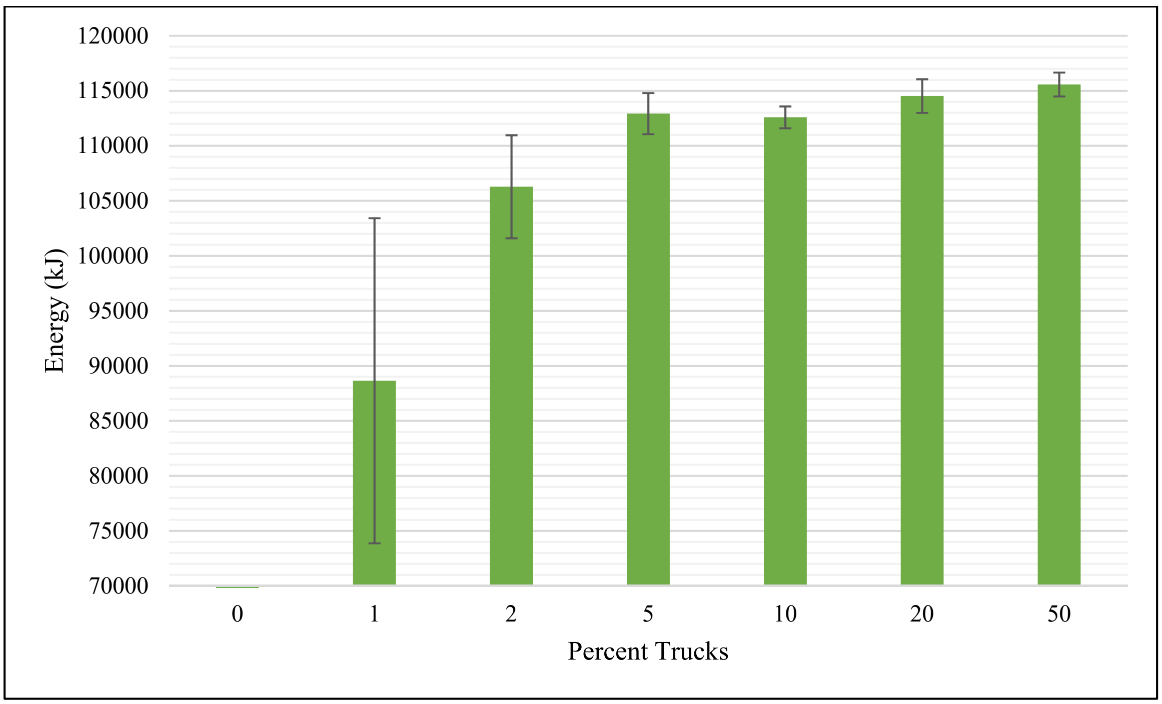

Figure 19: Average Energy for a Westbound Tractor Trailer

The average energy for the entire westbound fleet can be seen below in Figure 20. As a weighted average of all the energy data of all three vehicle types, it underwent the largest increase from 0% to 50% trucks, with the latter having a value 229% higher than the former. Unlike the three individual vehicle types, the fleet overall does have a statistically significant difference between the baseline of 0% trucks and the immediately higher level of 1% trucks. As the truck percentage increases, the average energy values begin to reflect the single unit truck and tractor trailer values. At 50% trucks, the mean energy value of the fleet is closer to that of single unit trucks than it is to that of passenger cars. The variability of the results increases alongside the truck percentage, with CIs of ±63 kJ and ±620 kJ at 0% trucks and 50% trucks respectively. The CI at 1% and 2% trucks can remain low despite the high variability of each truck type due to the overwhelming majority of passenger cars. As the truck percentage rises, resulting in the fleet wide statistics moving closer to the truck statistics, the decreasing truck variability results in a lower fleet wide variability compared to that of single unit trucks and tractor trailers at low truck percentages.

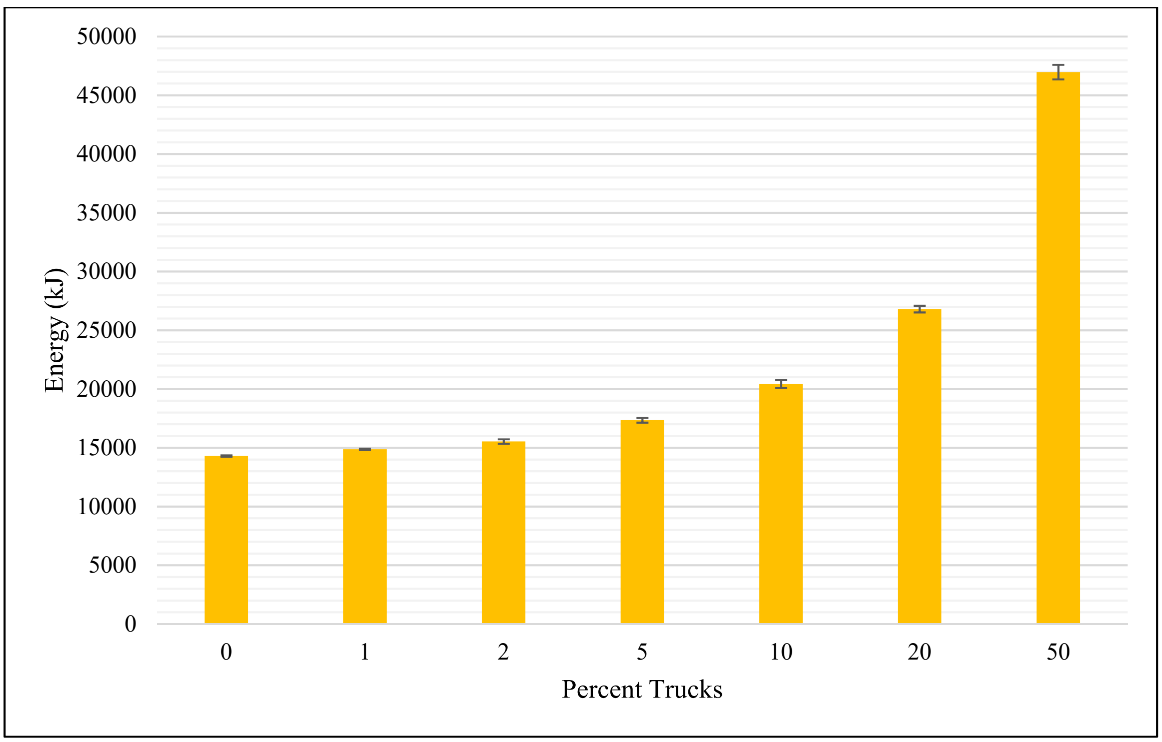

Figure 20: Average Energy for a Westbound Vehicle (Entire Fleet)

4.2 Eastbound Energy

The eastbound direction sees more traffic than the westbound direction during the afternoon rush hour period, likely due to commuters leaving the business districts around North Avenue for the residential areas east of the corridor. Higher traffic volumes may result in higher queueing, increased delays, and higher energy usage than those of the westbound direction.

The overall energy data for eastbound traffic can be found below in Figure 21. The overall patterns and relative values are similar to those of the westbound direction. The largest changes can be seen with tractor trailers at the lower truck percentages and with the weighted fleet average at the higher truck percentages. By comparison, the changes in passenger car and single unit truck energy use are minor. The highest variabilities are for tractor trailers at 1% and 2% trucks, though the variabilities are not as high as those of the westbound direction. As with the westbound direction, the variabilities generally decrease for single unit trucks and tractor trailers as the overall truck percentage increases.

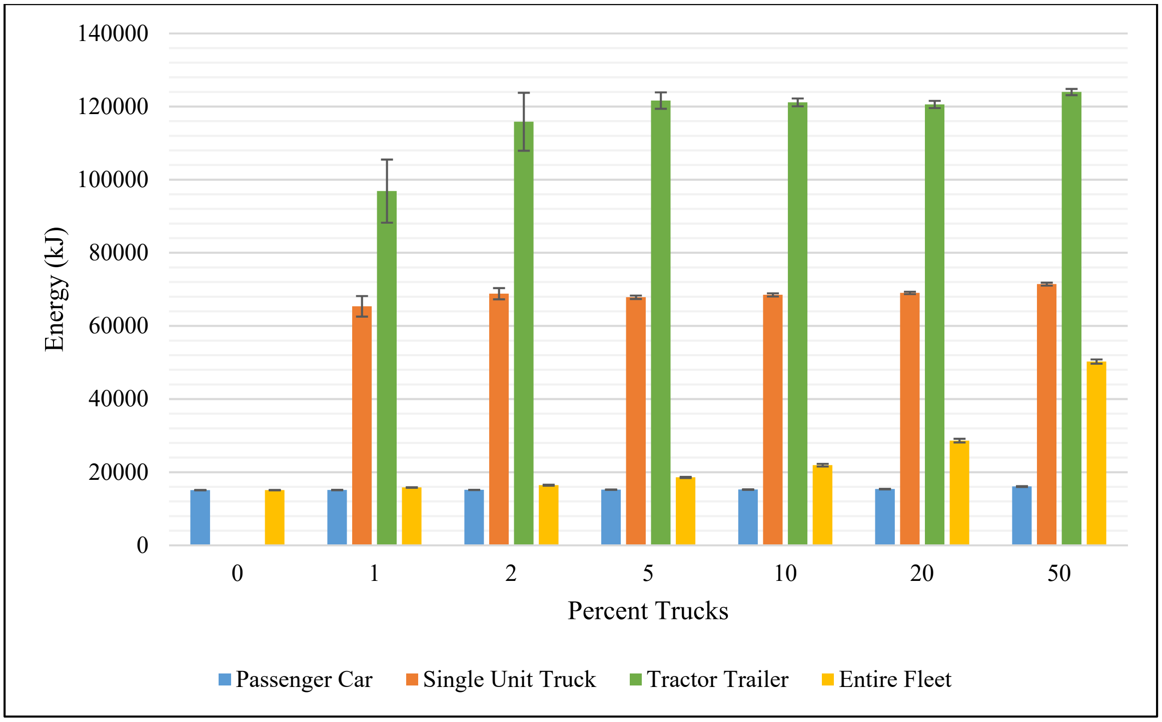

Figure 21: Average Energy on the North Avenue Corridor for Eastbound Vehicles

The energy data for eastbound passenger cars can be found below in Figure 22. As with the westbound passenger cars, statistically significantly different values relative to the baseline do not occur until the fleet reaches 5% trucks, with an increase of 0.72%. The largest increase from the baseline occurs at 50% trucks, and at 6.50% it is the only truck percentage in which an energy increase over 2% relative from the baseline occurs. Additionally, the increase in energy when moving from 20% trucks to 50% trucks is the only occurrence for eastbound passenger cars in which there is a statistically significant difference in energy values between two adjacent truck percentages.

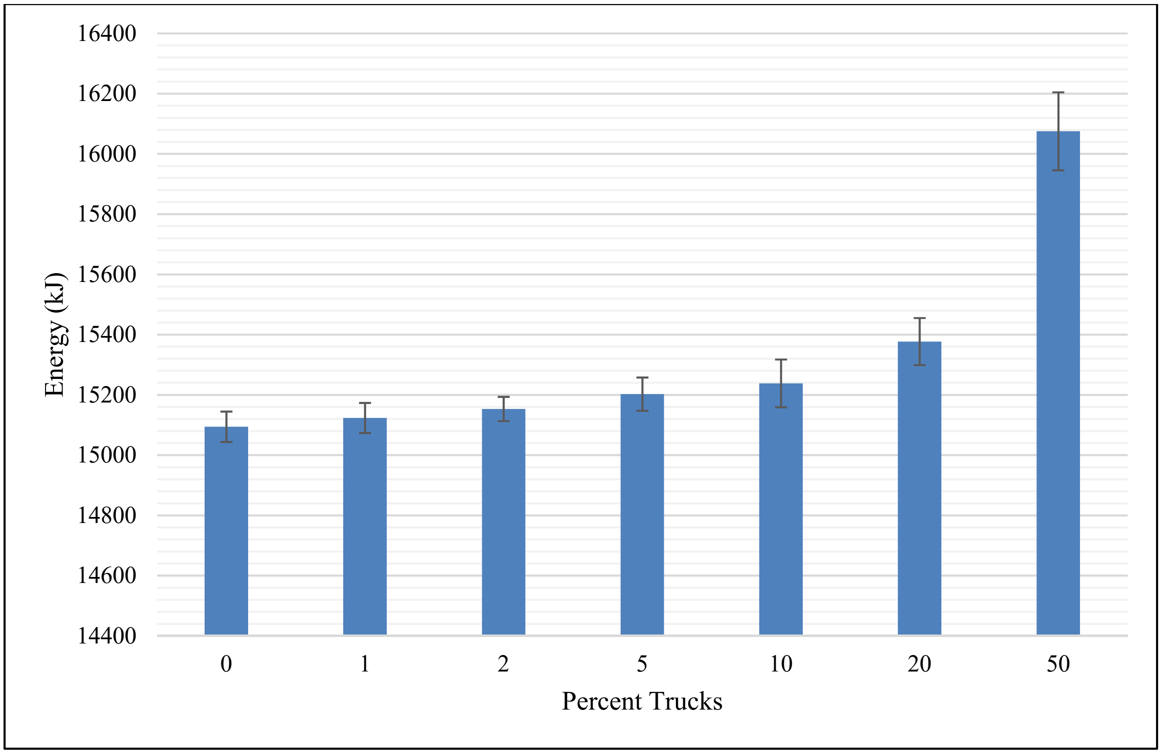

Figure 22: Average Energy for a Westbound Passenger Car

The energy data for westbound single unit trucks can be found below in Figure 23. As expected, single unit trucks saw an increase in both the mean and variability of energy compared to those of passenger cars. The lowest increase from the baseline of 1% trucks was 3.77%, and at 50% trucks, the mean energy was 9.28% higher than that of the baseline. This data set did not see the gradual but constant increase in mean energy as truck percentage also increased. The mean energy values for 5% trucks and 10% trucks were both lower than that of 2% trucks. The high variability of the values meant that the mean energies for 1% trucks through that of 20% trucks were not statistically significantly different from each other, despite an increase of 5.59% of the latter over the former.

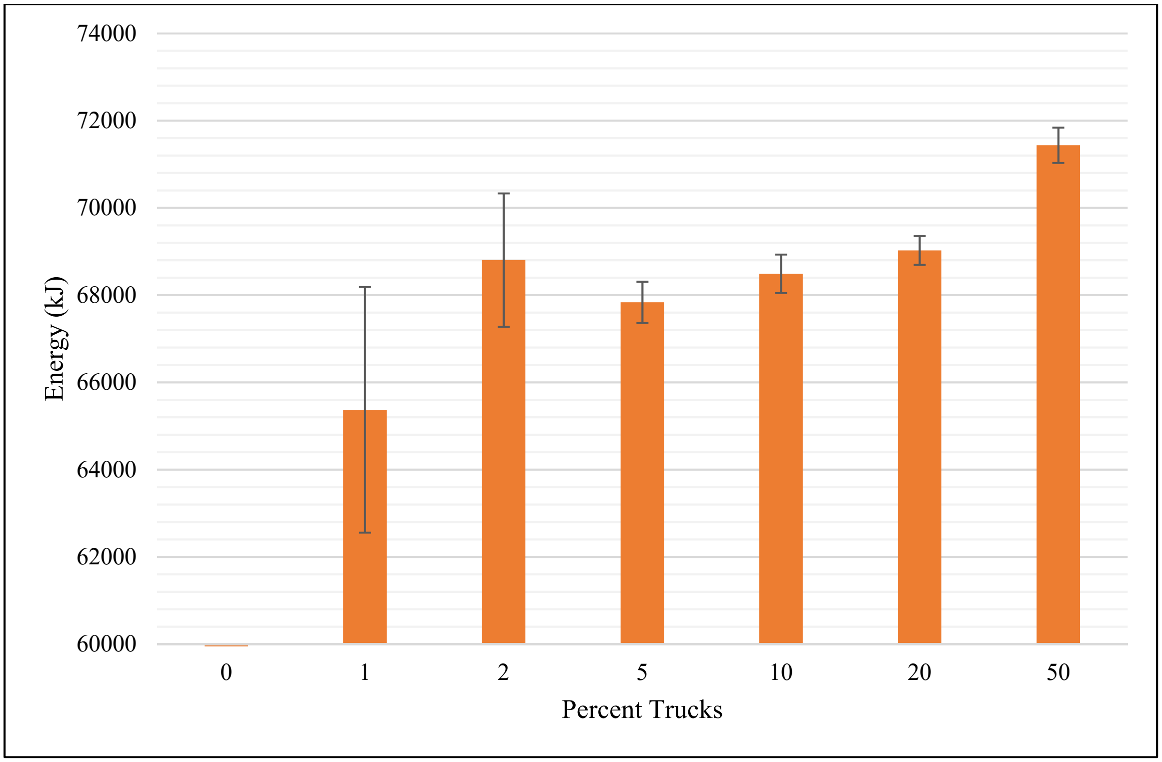

Figure 23: Average Energy for Eastbound Single Unit Trucks

The energy data for westbound tractor trailers can be found below in Figure 24. As expected after viewing the westbound energy data, tractor trailers had the highest mean energy and energy variability of the three vehicle types. The lowest energy increase from the baseline of 1% trucks was a 19.58% increase at 2% trucks, and from there it climbed to an increase of 27.97% at 50% trucks. Despite the large variabilities of ±8634 kJ and ±7928 kJ at 1% trucks and 2% trucks respectively, the increase in mean energy is enough to be statistically significantly different. As with eastbound single unit trucks, the increase was not constant. The energy increases from the baseline at 10% trucks and 20% trucks are smaller than that of 5% trucks. Despite this, the energy values from 2% through 20% are all not statistically different, keeping intact the overall increase in energy alongside the increase in truck percentage.

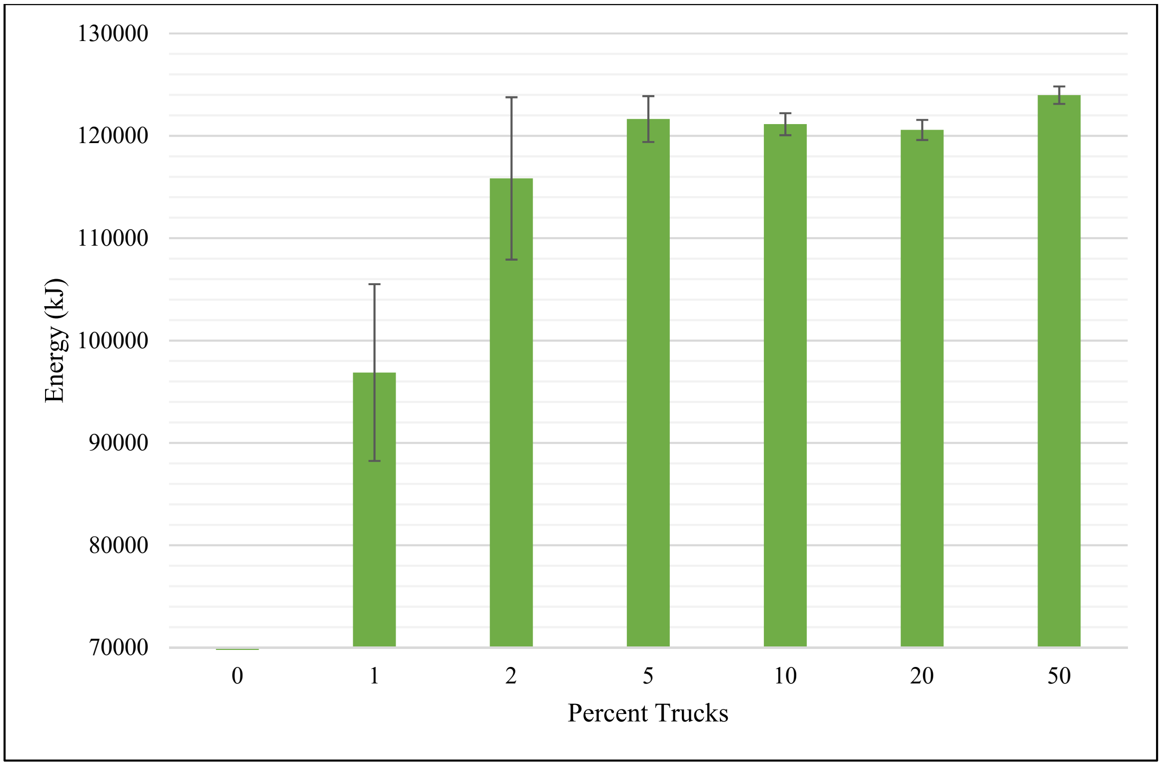

Figure 24: Average Energy for an Eastbound Tractor Trailer

The eastbound energy data for the entire fleet can be found below in Figure 25. Unlike any of the individual vehicle data, the fleet wide data sees statistically significant increases when comparing each truck percentage to the percentage immediately below it. This is due to the shifting nature of the fleet, as increasing the truck percentage brings with it both higher average values and higher variability. This hypothesis is backed up when considering the relationship between change in truck percentage and change in mean energy. For every percent increase in the truck percentage, there was an increase in the mean energy value relative to the baseline of approximately 4.5%.

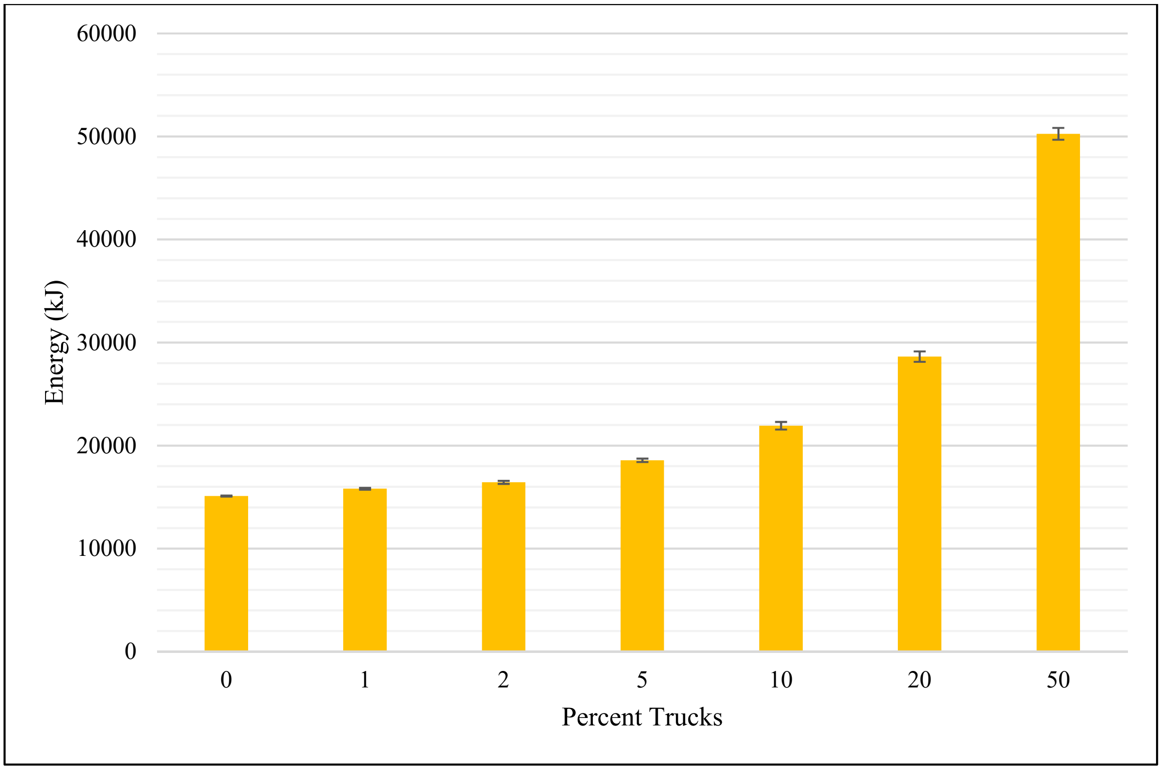

Figure 25: Average Energy for an Eastbound Vehicle (Entire Fleet)

4.3 Comparing Eastbound and Westbound Energy

As previously mentioned, differences in traffic flow between the eastbound and westbound directions have the potential to result in differing levels of mean energy and energy variation. More traffic may lead to more queueing and subsequently more energy, but may also lead to a larger sample size and therefore lower variability. The energy data sets for both directions have been analyzed in this section, but until now have not been directly compared. The graphs in this section will show the energy data in each direction alongside an average of the two.

The energy comparison for passenger cars can be seen below in Figure 26. It is immediately clear that the eastbound direction has higher per-vehicle energy, with a difference in mean values of approximately 800 kJ at the baseline that increases to just over 1,200 kJ at 50% trucks. The pattern of increasing energy alongside increasing truck percentage is not identical for eastbound and westbound. Eastbound energy has a more constant and gradual increase, while the westbound energy at times remains flat or slightly decreases before jumping back up in value. As discussed in previous sections, these slight decreases are within the 95% CIs, and can statistically be considered to have the effectively the same value. Each direction trades off having the larger variability as the truck percentage increases, and at 50% trucks, they are almost identical. Variability for passenger cars was relatively very small for both directions, and thus large differences between the two were not expected.

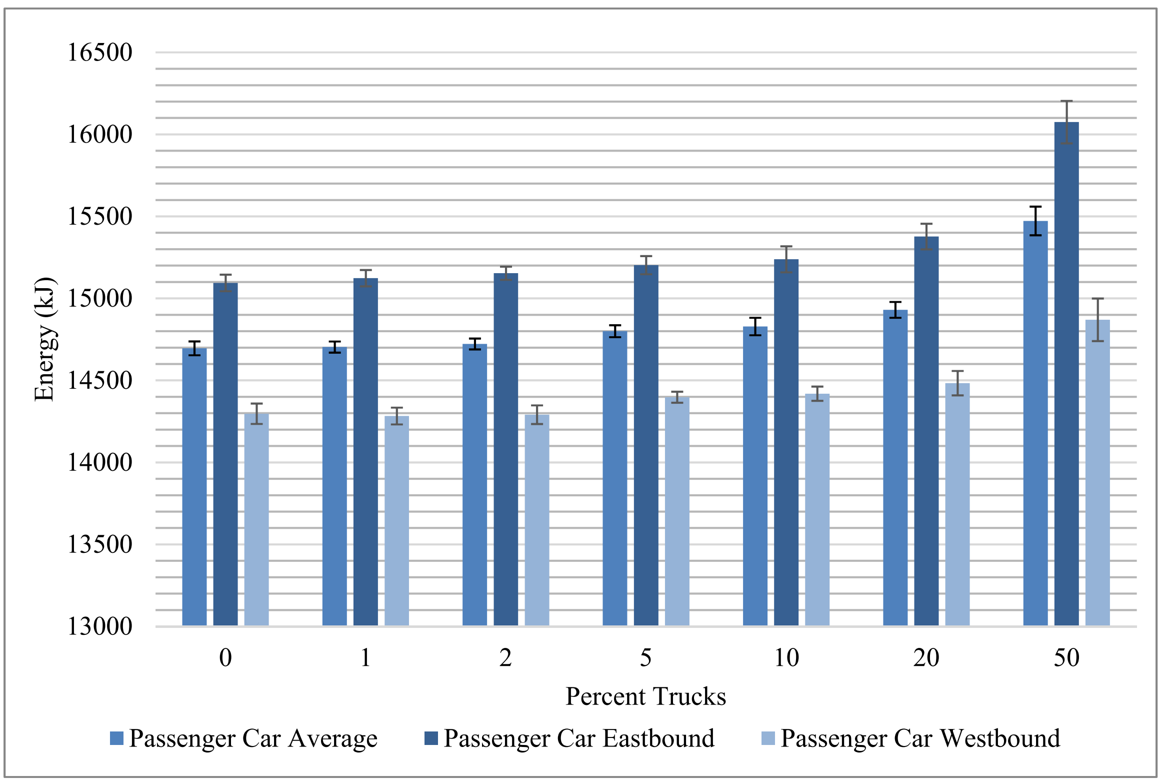

Figure 26: Average Energy Use by a Passenger Car

The energy data comparing each direction's single unit truck energy data can be found below in Figure 27. As with that of passenger cars, the eastbound mean energy values are higher at every truck percentage. Unlike that of passenger cars, the difference between those values is not constantly increasing, and is at its largest at 2% trucks before dropping in value. This may be due to the higher variability of single unit truck data relative to that of passenger cars. Similarly to that of passenger cars, the two directions of travel trade off having the higher variability. The eastbound direction has higher variability at the baseline and at 2% trucks, while the westbound has higher variability at 5% trucks. At higher truck percentages, westbound remains the direction with higher variability, but the difference in variability drops dramatically, with the ratio of variabilities dropping from 216% at 5% trucks to 7.1% at 20% trucks.

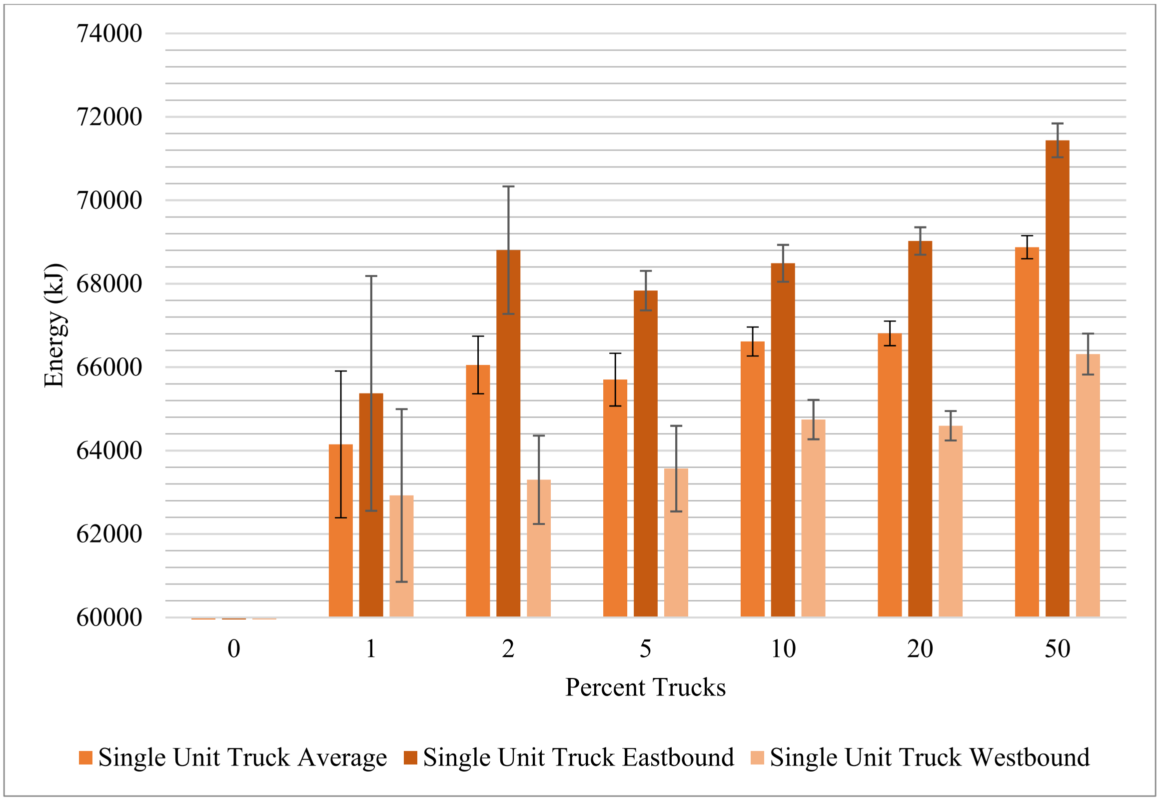

Figure 27: Average Energy Use by a Single Unit Truck

The energy data for tractor trailers can be seen below in Figure 28. Due to the high variability of tractor trailers, there is no statistical difference between the mean values of each direction at 1% trucks and 2% trucks. From 5% trucks through 50% trucks, the eastbound direction has a higher mean value, but the difference between the two means is not constantly increasing. In general, the westbound direction has the higher variability, with the exception being at 2% trucks. At 20% and 50% trucks, there is a more noticeable difference in variability between eastbound and westbound trucks when compared to that of passenger cars and single unit trucks.

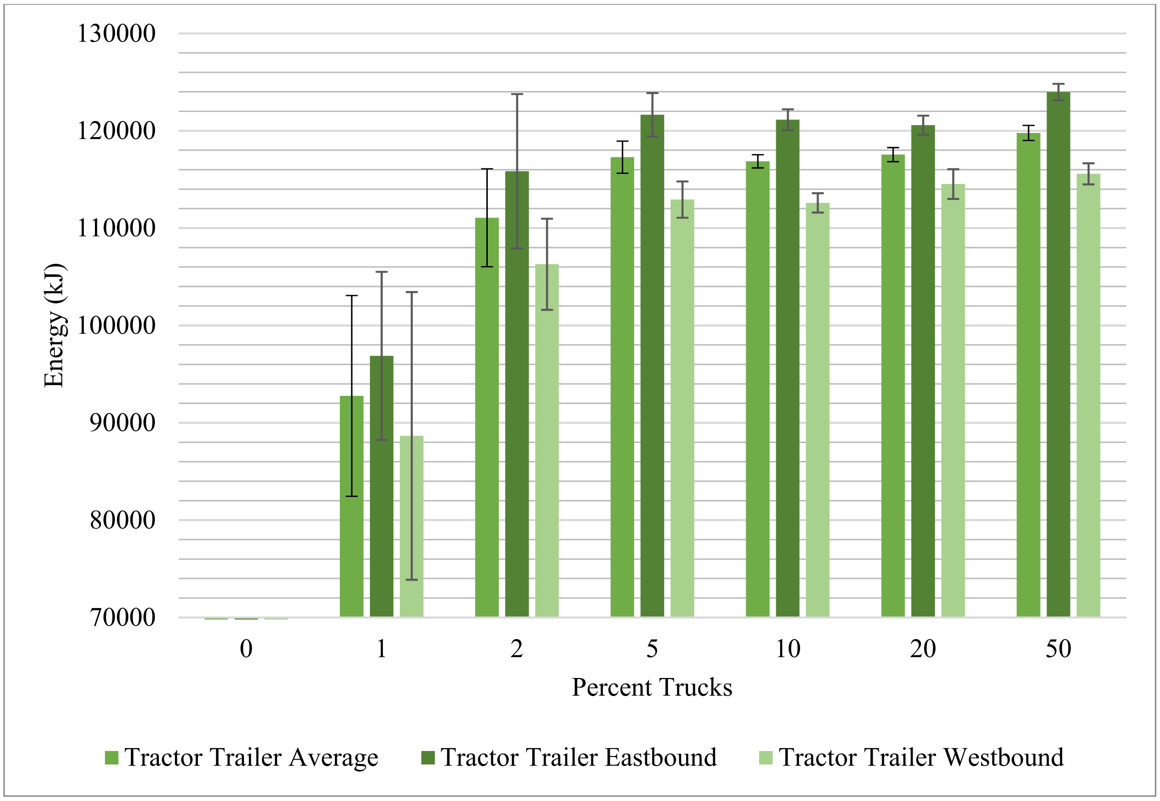

Figure 28: Average Energy Use by a Tractor Trailer

The energy data for the entire fleet can be found below in Figure 29. Due to the relatively low variabilities, there is an immediate statistical difference between the two directions' mean values, with eastbound holding a constant and increasing greater value over westbound. As with individual vehicle types, the two directional traffic flows trade off having the higher variability before evening out at 50% trucks. As mentioned in previous sections, the fleetwide data's low variability means that the difference in variability between the two directions is never large, maxing out at 216 kJ at 20% trucks.

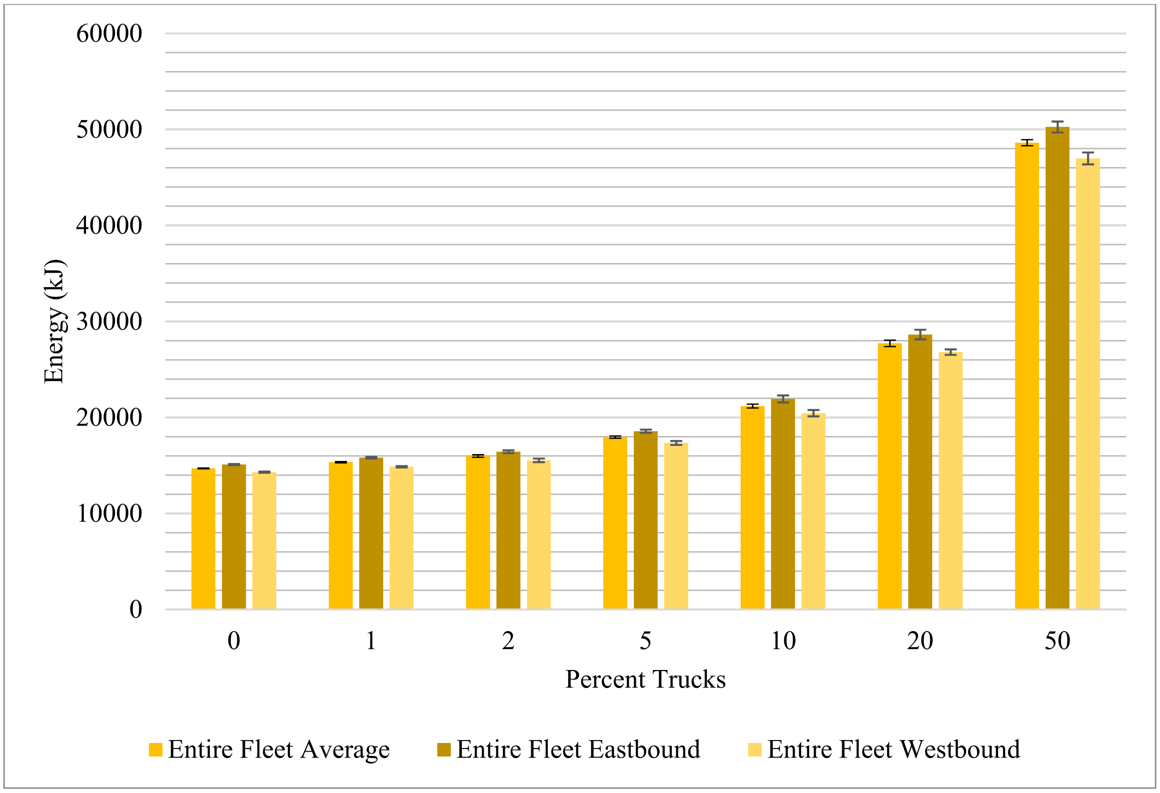

Figure 29: Average Energy Use for the Entire Fleet

4.4 Summary

Overall, increasing the truck percentage of the vehicle fleet resulted in an increase in per-vehicle energy use for every vehicle type as well as for the fleet wide average. Passenger cars had the smallest percentage increase of the three vehicle types, but due to its low variability had the lowest threshold for statistical significance. The westbound direction overall had lower per-vehicle energy values than the eastbound direction. It's been noted that the westbound direction also has lower traffic volumes than the eastbound, but more research is required in order to determine if this correlation brings with it any causation. Other differences such as grade, the number of stops, and signal timing could have an effect on the different directional values.

CHAPTER 5. CONCLUSION

When comparing the relationships between results of different fleet compositions, vehicle types, and direction of flow, there was an overall mixed bag of expected and unexpected results. Some relationships are clearly defined, while others are too variable to draw a conclusion.. These conclusions along with their justifications will be explained in this section. Alongside these conclusions are details of future research. This future research ranges from a simple retooling of this experiment to much larger experiments that can only be run when connected vehicles are in the field.

5.1 Effect of Truck Percentage on Energy

As mention in the results, shifting the fleet composition affected the energy usage of the fleet in an expected, proportional manner. For every percentage point that the truck composition increased, the energy output of the fleet increased by approximately 4.5%. The fleet wide energy levels had by far the most noticeable and predictable growth. As explained in the literature review, changing the fleet composition has a noticeable impact on fleet wide energy levels, as trucks use more energy on a per-vehicle basis compared to passenger cars. Also expected was the clear increase in vehicle variability. Each truck type had a higher variability than that of passenger cars, and even as increasing truck percentages resulted in decreasing truck variability, a combination of this and increasing car variability mean it can be concluded that increasing the truck percentage will increase the variability of the fleet wide energy levels.

As expected, increasing the truck percentage resulted in an increase of passenger car energy levels. Despite this, the increase was relatively small when compared to other vehicle types and the fleet wide average. Using the 95% confidence levels, no statistical difference from the baseline can be seen until the fleet reaches 5% trucks, and this difference is only 0.71%. Only in two sets of consecutive truck percentages could a statistical difference be drawn, showing that only when looking at cumulative changes can any differences be seen. At 10% trucks, the maximum expected truck percentage on North Avenue, the difference in passenger cars' energy levels is only 0.91% higher than that of the baseline. The threshold for what is considered to be a substantial or significant change can be a subjective one, but this change of under 1% can only be reasonably called such when only minor changes in energy usage are needed. With a 5.29% increase from the baseline, the 50% trucks fleet has a much larger change, showing that trucks driving in industrial corridors will see a larger difference in their energy usage than when driving on an urban arterial. With 95% confidence intervals all under ±100 kJ compared to mean values ranging from 14,700 kJ to 15,500 kJ, it can be concluded that a sample size of ten runs per fleet composition is adequate in order to determine a reasonably small range of energy data.

A statistical difference from the baseline does not occur for single unit trucks until the fleet composition reaches 10% trucks. At 10% trucks, the difference is 3.85%, larger than that of passenger cars at 20%. Like passenger cars, the increase in mean energy between consecutive fleet compositions is largest when moving from 20% trucks to 50% trucks. Additionally, this is the only set of consecutive fleet compositions that are statistically different from each other, showing that until truck percentages reach that of industrial corridors, statistical differences cannot be seen unless looking at cumulative differences between more than two fleet compositions. From this data, it can be concluded that single unit trucks on North Avenue will see a noticeable increase in energy usage only when the corridor is at its maximum truck percentage, and this increase will grow significantly when moved from North Avenue to an industrial corridor. With a confidence interval at the baseline of ±1758 kJ, it can be concluded that a sample size of ten runs per fleet composition is inadequate, and increasing said sample size will allow researchers to better determine what changes in energy are significant.

Of the three vehicle types, tractor trailers were most affected by the increase in truck percentage. When moving from the baseline of 1% trucks to the next fleet composition of 2% trucks, the mean energy increased by 19.73%. Despite the combined 95% CIs of these two truck percentages being ±15,349 kJ, the increase in mean value was found to be statistically significant. This was the only consecutive pair of fleet compositions found to be statistically different. This pattern was a departure from the increases seen in passenger cars and single unit trucks, as their rate of change increased alongside the truck percentage. This high jump is due to the relatively low baseline level, as further changes between pairs of fleet compositions more closely resemble those of other vehicle types. It can be concluded that increasing the truck percentage will result in an increase of tractor trailers' per-vehicle energy usage, but due to the high variability of the results at fleet compositions with low truck percentages, the severity of this increase cannot be fully determined. This high variability shows that a significant increase in the sample size must occur in order to be able to better interpret the results.

5.2 Effect of Travel Direction on Energy

As discussed in the results, it was expected that as the eastbound direction had higher traffic volumes than the westbound direction, it would have higher energy values due to increased queueing, congestion, and lower variability due to the higher traffic volumes giving it a larger sample size. The first of these hypotheses was found to be unanimously true. For every vehicle type and for every fleet composition, the per-vehicle energy output for eastbound vehicles was higher than that of westbound vehicles. For passenger cars, the difference between the two generally grew larger alongside truck percentage. This general increase is not as uniform for single unit trucks and tractor trailers, which see the gap between the two directions both grow and shrink as the truck percentage increases. This increase in average per-vehicle energy shows the potential effect that traffic volume can have on energy usage, but in-depth study is needed to further confirm this link. For instance, it is also possible that the signal coordination was more favorable to lower energy use in the westbound direction, result in the given observations. These and other potential confounding factor must explored in the next round of experiments.

Unlike with the average energy value, the higher variability did not always belong to one travel direction or the other. For passenger cars, the westbound direction has higher variabilities at lower truck percentages, but has the lower variability at higher truck percentages. At 50% trucks, the two directions even out, with 95% CIs only 0.2 kJ apart. This pattern of trading which direction has higher variability is also seen in single unit trucks, though for this vehicle type, the westbound direction maintains its lead at 50% trucks. The data is more consistent for tractor trailers, with westbound having the higher variability at almost every fleet composition. Tractor trailers also had the highest differences in variability between the two directions, likely due to the high variability of the vehicle type overall. The inconsistency of these results shows that a relationship between traffic volume and variability of results cannot be determined or even speculated upon without further in-depth research.

5.3 Future Research

This experiment has the potential to play an important role in future research in the near future and in the long term. The limitations of this experiment should be addressed in order to improve upon future experiments. Additionally, future research using the same framework as this experiment, as well as more complicated research involving field data collection should be explored.

5.3.1 Research Limitations

The significant limitation in this experiment was the sample size. The variability of single unit trucks and especially tractor trailers made data analysis difficult. While it was concluded that increasing the truck percentage will increase the per-vehicle energy use for trucks, the wide variability made researchers unable to determine the extent to which the increase would occur. In future research, this can be solved by significantly increasing the sample size and testing additional demand and signal control scenarios.

Another limitation was the large gaps between the fleet compositions with the largest truck percentages: 10%, 20%, and 50%. The largest energy differences were between fleet compositions of 10% and 20% trucks as well as 20% and 50% trucks, meaning more detail is needed in this range of truck percentages. This could be done by re-running the experiment looking at fleet compositions between 10% trucks and 50% truck at increments of 5% trucks.

Also, a limitation was the lack of unique vehicle models for different truck types. In VISSIM, acceleration and weight distributions are provided only for trucks overall, with no distributions for individual truck types. Weight distributions for single unit trucks and tractor trailers were created by using the weight classes for class 5 and class 8 trucks respectively. For this experiment, acceleration and speed distributions were not able to be created for the two different truck classes. Instead, the default acceleration distribution for trucks was used for each of the truck types, and the speed distribution created for trucks was used for each of the truck types.

5.3.2 Future Experiment Designs

This experiment considered only energy data. Future experiments have the potential to expand on this by analyzing the different GHG pollutants that the MOVES-Matrix can calculate. The framework of this experiment is already set up to do so, and it would allow researchers to look at the link between energy use and emissions output by a vehicle fleet.

Future analysis may also consider the three larger segments of the corridor. Although not looked at in this experiment, the data processing for this experiment already designated which small segments were in which of the three larger segments. In order for this analysis to happen, more analysis on how the fleet compositions differ between the three sections must be completed. These different fleet compositions may be a major driver in potentially differing energy results between the sections.

5.3.3 Long Term Research

In the long term, research has the potential to explore other ways in which connected vehicle data can be replicated and analyzed through VISSIM. As with this experiment, this research can help to determine the capabilities of connected vehicles while simulators able to work with connected vehicles are still in production. This experiment compared the energy data for each travel direction in order to determine if the difference in traffic volumes was a significant factor in the energy usage. This type of analysis can be expanded into its own experiment, with traffic volumes being changed similar to how truck percentages were changed in this experiment. Some of the experiments mentioned in the literature review varied traffic volume, but it was typically for an intersection or corridor built only for the experiment. None of them were based off of a real life corridor with actual traffic numbers, and as such only varied the traffic volumes by a pre-set increment. If such an experiment were to use North Avenue, then one way to vary the traffic volumes would be to assume a certain annual traffic growth rate, and run the model at traffic volumes that represent certain amounts of growth.

An additional potential experiment using replicated BSM data would be to replicate various market percentage rates by sampling the replicated BSM data. This could be done by adding a step in the data processing that randomly samples a pre-determined percentage of vehicles a pre-determined number of times. The energy data from this sample can then be normalized to that of a full fleet and compared to the data from the full fleet analysis. This information about expected sample error can help researchers, engineers, and manufacturers understand what level of market penetration of connected vehicles is needed in order to obtain reasonably accurate information about the entire fleet. Combining this with projected future market penetration rates and studies of different connected vehicle benefits at different market penetration rates, researchers may hold the potential to map out the safety, operational, and environmental benefits to connected vehicles as they become a larger part of the nationwide vehicular fleet.

Other long term research moves past connected vehicle replication and modelling and involves V2X technology deployed in both vehicles and infrastructure for field tests. These tests should include the aforementioned studies in order to study them in depth and compare the results with those of the simulated and mimicked connected vehicle experiments. This experiment was able to show to a certain extent how connected vehicle data can help measure changes in energy usage due to fleet changes, but using data from actual connected vehicles will help determine the accuracy of the experiment, showing researchers if changes to the experiment need to be made. This is especially important for sampling experiments, as it will allow engineers and policy makers to recalculate the timeline of connected vehicle benefits as more information and data becomes available. Connected vehicles in the field will also allow researchers to make sure the deployed hardware and software can take vehicular information and process it in real time, as failing to do this means none of the connected vehicle benefits can be realized.

APPENDIX A. SEGMENT NOMENCLATURE

Table 17: Intersection Segment IDs and Corresponding Streets

Segment ID	Cross Street	Northern Border	Eastern Border	Southern Border	Western Border
30	Northside Drive	31-001	30-001	32-001	20-005
60	State Street	61-001	60-001	62-001	30-015
70	Tech Pkwy	71-001	70-001	72-001	60-007
80	Techwood Dr.	81-001	80-001	82-001	70-011
90	Connector Ramp	91-001	90-001	92-001	80-005
100	Spring Street	101-001	100-001	102-001	90-007
110	West Peachtree	111-001	110-001	112-001	100-005
120	Peachtree St	121-001	120-001	122-001	110-007
130	Juniper St	131-001	130-001	132-001	120-005
140	Piedmont	141-001	140-001	142-001	130-005
150	Argonne	151-001	150-001	152-001	140-011
160	Hunt St	161-001	160-001	162-001	150-011
170	Parkway Drive	171-001	170-001	172-001	160-007
180	Boulevard	181-001	180-001	182-001	170-005
190	Glen Iris	191-001	190-001	192-001	180-011
200	PCM	201-001	200-001	202-001	190-007
210	Freedom Pkwy.	211-001	210-001	212-001	200-019

Table 18: Segment IDs and Lengths

Segment ID	Begin Point	Midpoint	End Point	Length (ft)
20-1	20-001	20-002	20-003	223
20-2	20-003	20-004	20-005	200
31-1	31-001	31-002	31-003	200
31-2	31-003	31-004	31-005	200
31-3	31-005	31-006	31-007	200
32-1	32-001	32-002	32-003	200
32-2	32-003	32-004	32-005	200
32-3	32-005	32-006	32-007	200
30-1	30-001	30-002	30-003	200
30-2	30-003	30-004	30-005	200
30-3	30-005	30-006	30-007	200
30-4	30-007	30-008	30-009	340
30-5	30-009	30-010	30-011	200
30-6	30-011	30-012	30-013	200
30-7	30-013	30-014	30-015	200
61-1	61-001	61-002	61-003	200
61-2	61-003	61-004	61-005	200
61-3	61-005	61-006	61-007	200
60-1	60-001	60-002	60-003	200
60-2	60-003	60-004	60-005	358
60-3	60-005	60-006	60-007	200
71-1	71-001	71-002	71-003	200
71-2	71-003	71-004	71-005	200
71-3	71-005	71-006	71-007	200
72-1	72-001	72-002	72-003	200
72-2	72-003	72-004	72-005	200
72-3	72-005	72-006	72-007	200
70-1	70-001	70-002	70-003	200
70-2	70-003	70-004	70-005	200
70-3	70-005	70-006	70-007	309
70-4	70-007	70-008	70-008	200
70-5	70-009	70-010	70-011	200
81-1	81-001	81-002	81-003	200
81-2	81-003	81-004	81-005	200
81-3	81-005	81-006	81-007	200
82-1	82-001	82-002	82-003	200
82-2	82-003	82-004	82-005	200

82-3	82-005	82-006	82-007	200
80-1	80-001	80-002	80-003	144
80-2	80-003	80-004	80-005	144
91-1	91-001	91-002	91-003	200
91-2	91-003	91-004	91-005	200
91-3	91-005	91-006	91-007	200
90-1	90-001	90-002	90-003	200
90-2	90-003	90-004	90-005	76
90-3	90-005	90-006	90-007	200
101-1	101-001	101-002	101-003	200
101-2	101-003	101-004	101-005	200
101-3	101-005	101-006	101-007	200
102-1	102-001	102-002	102-003	200
102-2	102-003	102-004	102-005	200
102-3	102-005	102-006	102-007	200
100-1	100-001	100-002	100-003	166
100-2	100-003	100-004	100-005	166
111-1	111-001	111-002	111-003	200
111-2	111-003	111-004	111-005	200
111-3	111-005	111-006	111-007	200
112-1	112-001	112-002	112-003	200
112-2	112-003	112-004	112-005	200
112-3	112-005	112-006	112-007	200
110-1	110-001	110-002	110-003	200
110-2	110-003	110-004	110-005	231
110-3	110-005	110-006	110-007	200
121-1	121-001	121-002	121-003	200
121-2	121-003	121-004	121-005	200
121-3	121-005	121-006	121-007	200
122-1	122-001	122-002	122-003	200
122-2	122-003	122-004	122-005	200
122-3	122-005	122-006	122-007	200
120-1	120-001	120-002	120-003	175
120-2	120-003	120-004	120-005	175
131-1	131-001	131-002	131-003	200
131-2	131-003	131-004	131-005	200
131-3	131-005	131-006	131-007	142
132-1	132-001	132-002	132-003	200
132-2	132-003	132-004	132-005	200
132-3	132-005	132-006	132-007	200
130-1	130-001	130-002	130-003	188

130-2	130-003	130-004	130-005	188
141-1	141-001	141-002	141-003	200
141-2	141-003	141-004	141-005	200
141-3	141-005	141-006	141-007	200
142-1	142-001	142-002	142-003	200
142-2	142-003	142-004	142-005	200
142-3	142-005	142-006	142-007	200
140-1	140-001	140-002	140-003	200
140-2	140-003	140-004	140-005	200
140-3	140-005	140-006	140-007	349
140-4	140-007	140-008	140-009	200
140-5	140-009	140-010	140-011	200
151-1	151-001	151-002	151-003	200
151-2	151-003	151-004	151-005	200
151-3	151-005	151-006	151-007	200
152-1	152-001	152-002	152-003	200
152-2	152-003	152-004	152-005	200
152-3	152-005	152-006	152-007	200
150-1	150-001	150-002	150-003	200
150-2	150-003	150-004	150-006	222
150-3	150-006	150-008	150-009	223
150-4	150-009	150-010	150-011	200
161-1	161-001	161-002	161-003	200
161-2	161-003	161-004	161-005	200
161-3	161-005	161-006	161-007	200
162-1	162-001	162-002	162-003	200
162-2	162-003	162-004	162-005	200
162-3	162-005	162-006	162-007	200
160-1	160-001	160-002	160-003	200
160-2	160-003	160-004	160-005	128
160-3	160-005	160-006	160-007	200
171-1	171-001	171-002	171-003	200
171-2	171-003	171-004	171-005	200
171-3	171-005	171-006	171-007	200
172-1	172-001	172-002	171-003	200
172-2	172-003	172-004	172-005	200
172-3	172-005	172-006	172-007	200
170-1	170-001	170-003	170-005	222
181-1	181-001	181-002	181-003	200
181-2	181-003	181-004	181-005	200
181-3	181-005	181-006	181-007	200

182-1	182-001	182-002	182-003	200
182-2	182-003	182-004	182-005	200
182-3	182-005	182-006	182-007	200
180-1	180-001	180-002	180-003	200
180-2	180-003	180-004	180-005	200
180-3	180-005	180-006	180-007	357
180-4	180-007	180-008	180-009	200
180-5	180-009	180-010	180-011	200
191-1	191-001	191-002	191-003	200
191-2	191-003	191-004	191-005	200
191-3	191-005	191-006	191-007	200
192-1	192-001	192-002	192-003	200
192-2	192-003	192-004	192-005	200
192-3	192-005	192-006	192-007	200
190-1	190-001	190-002	190-003	200
190-2	190-003	190-004	190-005	70
190-3	190-005	190-006	190-007	200
201-1	201-001	201-002	201-003	200
201-2	201-003	201-004	201-005	200
201-3	201-005	201-006	201-007	200
202-1	202-001	202-002	202-003	200
202-2	202-003	202-004	202-005	200
202-3	202-005	202-006	202-007	200
200-1	200-001	200-002	200-003	200
200-2	200-003	200-004	200-005	200
200-3	200-005	200-006	200-007	200
200-4	200-007	200-008	200-009	200
200-5	200-009	200-010	200-011	216
200-6	200-011	200-012	200-013	200
200-7	200-013	200-014	200-015	200
200-8	200-015	200-016	200-017	200
200-9	200-017	200-018	200-019	200
211-1	211-001	211-002	211-003	200
211-2	211-003	211-004	211-005	200
211-3	211-005	211-006	211-007	200
212-1	212-001	212-002	212-003	200
212-2	212-003	212-004	212-005	200
212-3	212-005	212-006	212-007	200
210-1	210-001	210-002	210-003	200
210-2	210-003	210-004	210-005	152
210-3	210-005	210-006	210-007	200

APPENDIX B. ENERGY TABLES

This appendix contains the tables showing the mean energy, 95% CI, and change from the baseline for eastbound vehicles, westbound vehicles, and an average of the two directions at each fleet composition.

Table 19: Energy Data for Westbound Passenger Cars

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	14296.56	0.00%	62.29	N/A	N/A
1	14282.83	-0.10%	51.32	NO	NO
2	14290.81	-0.04%	57.02	NO	NO
5	14397.31	0.70%	33.62	YES	YES
10	14418.84	0.86%	43.30	YES	NO
20	14483.07	1.30%	74.28	YES	NO
50	14869.41	4.01%	129.71	YES	YES

Table 20: Energy Data for Westbound Single Unit Trucks

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	0	N/A	N/A	N/A	N/A
1	62924.22	0%	2069.92	N/A	N/A
2	63299.38	0.60%	1058.78	NO	NO
5	63567.52	1.02%	1026.58	NO	NO
10	64742.27	2.89%	471.99	NO	NO
20	64594.92	2.66%	353.21	NO	NO
50	66313.21	5.39%	490.56	YES	YES

Table 21: Energy Data for Westbound Tractor Trailers

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	0	N/A	N/A	N/A	N/A
1	88647.52	0%	14776.91	N/A	N/A
2	106282.97	19.89%	4682.75	NO	NO
5	112929.11	27.39%	1867.42	YES	YES
10	112588.82	27.01%	995.00	YES	NO
20	114523.57	29.19%	1530.59	YES	NO
50	115572.17	30.37%	1083.67	YES	NO

Table 22: Energy Data for Westbound Vehicles for the Entire Fleet

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	14296.56	0%	62.29	N/A	N/A
1	14862.89	3.96%	67.98	YES	YES
2	15530.65	8.63%	187.85	YES	YES
5	17339.78	21.29%	202.11	YES	YES
10	20439.22	42.97%	332.34	YES	YES
20	26803.49	87.48%	288.35	YES	YES
50	46974.07	228.57%	619.94	YES	YES

Table 23: Energy Data for Eastbound Passenger Cars

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	15094.19	0.00%	50.41	N/A	N/A
1	15123.24	0.19%	49.93	NO	NO
2	15153.25	0.39%	40.31	NO	NO
5	15202.50	0.72%	55.24	YES	NO
10	15238.26	0.95%	79.27	YES	NO
20	15376.95	1.87%	78.13	YES	NO
50	16074.91	6.50%	129.51	YES	YES

Table 24: Energy Data for Eastbound Single Unit Trucks

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	0	N/A	N/A	N/A	N/A
1	65370.94	0%	2814.62	N/A	N/A
2	68804.18	5.25%	1528.05	NO	NO
5	67834.65	3.77%	474.02	NO	NO
10	68488.74	4.77%	441.61	NO	NO
20	69023.94	5.59%	329.71	YES	NO
50	71435.92	9.28%	405.45	YES	YES

Table 25: Energy Data for Eastbound Tractor Trailers

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	0	N/A	N/A	N/A	N/A
1	96871.27	0%	8634.08	N/A	N/A
2	115835.61	19.58%	7928.79	YES	YES
5	121633.41	25.56%	2239.20	YES	NO
10	121133.79	25.05%	1072.02	YES	NO
20	120567.54	24.46%	980.66	YES	NO
50	123967.34	27.97%	852.75	YES	YES

Table 26: Energy Data for Eastbound Vehicles for the Entire Fleet

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	15094.19	0%	50.41	N/A	N/A
1	15810.14	4.74%	85.44	YES	YES
2	16429.85	8.85%	147.46	YES	YES
5	18567.84	23.01%	168.06	YES	YES
10	21925.32	45.26%	366.02	YES	YES
20	28631.38	89.68%	504.76	YES	YES
50	50254.27	232.94%	572.32	YES	YES

Table 27: Bidirectional Average Energy Data for Passenger Cars

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	14695.37	0.00%	42.41	0	0
1	14703.04	0.05%	33.94	NO	NO
2	14722.03	0.18%	33.00	NO	NO
5	14799.90	0.71%	36.22	YES	YES
10	14828.55	0.91%	53.23	YES	NO
20	14930.01	1.60%	48.27	YES	NO
50	15472.16	5.29%	87.35	YES	YES

Table 28: Bidirectional Average Energy Data for Single Unit Trucks

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	0	N/A	N/A	N/A	N/A
1	64147.58	0%	1758.13	N/A	N/A
2	66051.78	2.97%	690.77	NO	NO
5	65701.09	2.42%	632.49	NO	NO
10	66615.51	3.85%	347.14	YES	NO
20	66809.43	4.15%	294.05	YES	NO
50	68874.57	7.37%	276.52	YES	YES

Table 29: Bidirectional Average Energy Data for Tractor Trailers

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	0	N/A	N/A	N/A	N/A
1	92759.39	0%	10316.28	N/A	N/A
2	111059.29	19.73%	5032.81	YES	YES
5	117281.26	26.44%	1652.56	YES	NO
10	116861.30	25.98%	681.48	YES	NO
20	117545.56	26.72%	723.94	YES	NO
50	119769.76	29.12%	771.82	YES	NO

Table 30: Bidirectional Average Energy Data for the Entire Fleet

Truck %	Mean Energy (kJ)	% Increase from Baseline	95% CI (± kJ)	Stat. Sig. with Baseline?	Stat. Sig. with Adjacent?
0	14695.37	0%	42.41	0	0
1	15336.52	4.36%	66.37	YES	YES
2	15980.25	8.74%	131.02	YES	YES
5	17953.81	22.17%	115.42	YES	YES
10	21182.27	44.14%	202.56	YES	YES
20	27717.43	88.61%	333.80	YES	YES
50	48614.17	230.81%	320.32	YES	YES

APPENDIX C. SCRIPTS

Script 1: FZP_Condensation. This script condenses the 10 Hz Vehicle Record File into a 1 Hz file

```
import numpy as np
import statistics as st
from pyproj import Proj, transform
from shutil import copyfile

dg_proj = Proj(init='epsg:4269')
ga_proj = Proj(init='epsg:2240')
# feet to meter
f_m = 0.3048006096012192
StartTime=900.1

def getType(length):
    char=['PC','B','SU','TT']
    if(length>10 and length<18):
        return 'PC'
    elif(length>35 and length<45):
        return 'B'
    elif(length>25 and length<35):
```

```
        return 'SU'
    elif(length>50 and length<60):
        return 'TT'


copyfile("NorthAveCondensedData_Intro.fzp", "NorthAveCondensedData.fzp")
CarList=[]; CarLen=[]; CarGrade=[]; CarBear=[]; CarTime=[]; CarDist=[]
CarX=[]; CarY=[]; CarZ=[]; CarSpeed=[]; CarAccl=[]
with open("NorthAveCondensedData.fzp",'a+') as file:
    m=0
    with open("North Ave Corridor PM_Initial_Grade_001.fzp") as infile:
        for line in infile:
            f=line.split('\n')
            f=f[0].split(';')
            try:
                float(f[0])
            except ValueError:
                continue
            m+=1
            print(m)
            t=float(f[0])-StartTime; vN=int(f[2]); XYZ=f[4].split(); XYZ1=f[3].split()
            X=float(XYZ[0]); Y=float(XYZ[1]); Z=float(XYZ[2]); X1=float(XYZ1[0]); Y1=float(XYZ1[1]); Z1=float(XYZ1[2])
            speed=float(f[5]); accl=float(f[6]); length=float(f[9])
```

```
bearing=180/np.pi*((X>X1)*np.pi + (X<=X1 and Y>Y1)*2*np.pi + (np.arctan((Y1-Y)/(X1-X)) if X1!=X else np.pi*np.sign(Y1-Y)/2))
X=(X+X1)/2; Y=(Y+Y1)/2; Z=(Z+Z1)/2
if not vN in CarList:
  CarList.append(vN); CarLen.append(length); CarDist.append(0.0); CarGrade.append(0.0); CarTime.append([t])
  CarX.append([X]); CarY.append([Y]); CarZ.append([Z]); CarSpeed.append([speed]); CarAccl.append([accl]); CarBear.append([bearing])
else:
  j=CarList.index(vN)
  CarTime[j].append(t)
  if len(CarX[j])>0:
    CarDist[j]+=((CarX[j][-1]-X)**2 + (CarY[j][-1]-Y)**2)**.5
  CarX[j].append(X); CarY[j].append(Y); CarZ[j].append(Z); CarSpeed[j].append(speed); CarAccl[j].append(accl); CarBear[j].append(bearing)
j=CarList.index(vN)
if round(CarTime[j][-1]*10)%10==9:
  time=int(np.floor(CarTime[j][0])); frac=float(len(CarTime[j]))/10
  X=st.median(CarX[j]); Y=st.median(CarY[j]); speed=st.median(CarSpeed[j]); accl=st.median(CarAccl[j]); bear=st.median(CarBear[j])
  Lat=transform(ga_proj,dg_proj, X+2224260.0*f_m,Y+1371320.0*f_m)[1]
  Long=transform(ga_proj,dg_proj, X+2224260.0*f_m,Y+1371320.0*f_m)[0]
  Grade=CarGrade[j]
```

```
                if CarDist[j]>0.0:
                    Grade=(CarZ[j][-1]-CarZ[j][0])/CarDist[j]
                CarTime[j]=[];   CarX[j]=[];   CarY[j]=[];   CarZ[j]=[];   CarSpeed[j]=[];
CarAccl[j]=[]; CarBear[j]=[]; CarDist[j]=0.0; CarGrade[j]=Grade

file.write(str(time)+';'+str(vN)+';'+getType(length)+';'+str(Lat)+';'+str(Long)+';'+str(speed
)+';'+str(accl)+';'+str(frac)+';'+str(Grade)+';'+str(bear)+';\n')

    for j in range(0,len(CarList)):
        if len(CarTime[j])>0:
            time=int(np.floor(CarTime[j][0])); frac=float(len(CarTime[j]))/10
            X=st.median(CarX[j]);   Y=st.median(CarY[j]);   speed=st.median(CarSpeed[j]);
accl=st.median(CarAccl[j]); bear=st.median(CarBear[j])
            Lat=transform(ga_proj,dg_proj, X+2224260.0*f_m,Y+1371320.0*f_m)[1]
            Long=transform(ga_proj,dg_proj, X+2224260.0*f_m,Y+1371320.0*f_m)[0]
            Grade=CarGrade[j]
            if CarDist[j]>0.0:
                Grade=(CarZ[j][-1]-CarZ[j][0])/CarDist[j]

file.write(str(time)+';'+str(CarList[j])+';'+getType(CarLen[j])+';'+str(Lat)+';'+str(Long)+';'
+str(speed)+';'+str(accl)+';'+str(frac)+';'+str(Grade)+';'+str(bear)+';\n')
```

Script 2: EnergyCalculation_SegmentAssociation. This script takes each line of the condensed vehicle record file, calculates the energy use, and places it in the segment that the vehicle is located in.

```
import csv
from pyproj import Proj, transform
from shutil import copyfile


dg_proj = Proj(init='epsg:4269')
ga_proj = Proj(init='epsg:2240')


# feet to meter


f_m = 0.3048006096012192




def getBin(speed, accl, VSP):
    if accl <= -2.0:
        return 0
    elif speed < 1.0:
        return 1
    elif speed < 25:
        if VSP < 0:
            return 11
```

```
    elif VSP < 3:
        return 12
    elif VSP < 6:
        return 13
    elif VSP < 9:
        return 14
    elif VSP < 12:
        return 15
    else:
        return 16
elif speed < 50:
    if VSP < 0:
        return 21
    elif VSP < 3:
        return 22
    elif VSP < 6:
        return 23
    elif VSP < 9:
        return 24
    elif VSP < 12:
        return 25
    elif VSP < 18:
        return 27
```

```
        elif VSP < 24:
            return 28
        elif VSP < 30:
            return 29
        else:
            return 30
    else:
        if VSP < 6:
            return 33
        elif VSP < 12:
            return 35
        elif VSP < 18:
            return 37
        elif VSP < 24:
            return 38
        elif VSP < 30:
            return 39
        else:
            return 40


def getEnergy(
    Speed,
```

```
Accl,
VType,
grade, frac
):
char = ['PC', 'B', 'SU', 'TT']
A = [0.156461, 1.03968, 0.596526, 1.47389]
B = [0.002001, 0, 0, 0]
C = [0.000492, 0.003587, 0.001603, 0.003681]
M = [1.4788, 17.1, 17.1, 17.1]
m = [1.4788, 16.556, 8.5389, 24.419]
g = 9.81
v = 0.44704*Speed
acc = 0.44704*Accl
j = char.index(VType)
VSP = A[j] / M[j] * v + B[j] / M[j] * v ** 2 + C[j] / M[j] * v ** 3 \
  + m[j] / M[j] * (acc + g * grade) * v
Bin = getBin(Speed, Accl, VSP)
BinDetails = list(map(list,
             zip(*list(csv.reader(open('EnergyEmissions_'
             + VType + '_2017.csv'))))))
enchar=''
for i in range(8):
  enchar+=str(float(BinDetails[i+ 1][BinDetails[0].index(str(Bin))])*frac/3600.0)+';'
```

```
    enchar+=str(Speed)+';'+str(Accl)+';'+str(VSP)+';'
    return enchar


def assignLink(
    X,
    Y,
    ID,
    i_d,
    Extreme,
    ):
    i = ID.index(i_d)
    a = Extreme[i][0]
    b = Extreme[i][1]
    c = Extreme[i][2]
    d = Extreme[i][3]
    if d == b:
        Q1 = abs(X - a)
        Q2 = abs(X - c)
        Q3 = abs(Y - d)
    else:
        S = (a - c) / (d - b)
        Q1 = abs(S * X - Y - a * S + b) / (S ** 2 + 1) ** .5
```

```
        Q2 = abs(S * X - Y - c * S + d) / (S ** 2 + 1) ** .5
        Q3 = abs(X + S * Y - c - S * d) / (S ** 2 + 1) ** .5
    if Q1 < Extreme[i][4] and Q2 < Extreme[i][4] and Q3 < 60:
        return 1
    return 0


def assignIntersection(
    X,
    Y,
    ID1,
    i_d,
    Extreme1,
    ):
    i = ID1.index(i_d)
    a = Extreme1[i][0]
    b = Extreme1[i][1]
    c = Extreme1[i][2]
    d = Extreme1[i][3]
    if d == b:
        Q1 = abs(X - a)
        Q2 = abs(X - c)
    else:
```

```
        S = (a - c) / (d - b)
        Q1 = abs(S * X - Y - a * S + b) / (S ** 2 + 1) ** .5
        Q2 = abs(S * X - Y - c * S + d) / (S ** 2 + 1) ** .5
    a = Extreme1[i][5]
    b = Extreme1[i][6]
    c = Extreme1[i][7]
    d = Extreme1[i][8]
    if d == b:
        Q3 = abs(X - a)
        Q4 = abs(X - c)
    else:
        S = (a - c) / (d - b)
        Q3 = abs(S * X - Y - a * S + b) / (S ** 2 + 1) ** .5
        Q4 = abs(S * X - Y - c * S + d) / (S ** 2 + 1) ** .5
    if Q1 < Extreme1[i][4] and Q2 < Extreme1[i][4] and Q3 \
        < Extreme1[i][9] and Q4 < Extreme1[i][9]:
        return 1
    return 0


def getSegment(
    X,
    Y,
```

```
SegID,
ID,
Extreme,
ID1,
Extreme1,
Adjacent,
Flag,
):
if Flag != '0':
    if len(Flag.split('-')) == 2:
        if assignLink(X, Y, ID, Flag, Extreme) == 1:
            return [1, Flag]
    if len(Flag.split('-')) == 1:
        if assignIntersection(X, Y, ID1, Flag, Extreme1) == 1:
            return [1, Flag]
    for j in Adjacent[SegID.index(Flag)]:
        if len(j.split('-')) == 2:
            if assignLink(X, Y, ID, j, Extreme) == 1:
                return [1, j]
        else:
            if assignIntersection(X, Y, ID1, j, Extreme1) == 1:
                return [1, j]
for i in SegID:
```

```
        if len(i.split('-')) == 2:
            if assignLink(X, Y, ID, i, Extreme) == 1:
                return [1, i]
        else:
            if assignIntersection(X, Y, ID1, i, Extreme1) == 1:
                return [1, i]
    return [0, 0]



Nodes = list(map(list,
             zip(*list(csv.reader(open('NorthAveNodeDetails.csv'
             )))[1:])))
SegID = []
ID = []
Extreme = []
with open('NorthAveLinkDetails.csv') as file:
    for line in file:
        f = line.split(',')
        ID.append(f[0])
        SegID.append(f[0])
        j1 = Nodes[0].index(f[1])
        j2 = Nodes[0].index(f[3])
        a = float(Nodes[1][j1])
```

```
        b = float(Nodes[2][j1])

        c = float(Nodes[1][j2])

        d = float(Nodes[2][j2])

        dist = ((a - c) ** 2 + (b - d) ** 2) ** .5

        Extreme.append([a, b, c, d, dist])


ID1 = []

Extreme1 = []

with open('NorthAveIntersectionDetails.csv') as file:

    for line in file:

        f = line.split('\n')

        f = f[0].split(',')

        ID1.append(f[0])

        SegID.append(f[0])

        j1 = Nodes[0].index(f[2])

        j2 = Nodes[0].index(f[4])

        a = float(Nodes[1][j1])

        b = float(Nodes[2][j1])

        c = float(Nodes[1][j2])

        d = float(Nodes[2][j2])

        dist = ((a - c) ** 2 + (b - d) ** 2) ** .5

        j11 = Nodes[0].index(f[3])

        j12 = Nodes[0].index(f[5])
```

```
        a1 = float(Nodes[1][j11])
        b1 = float(Nodes[2][j11])
        c1 = float(Nodes[1][j12])
        d1 = float(Nodes[2][j12])
        dist1 = ((a1 - c1) ** 2 + (b1 - d1) ** 2) ** .5
        Extreme1.append([
            a,
            b,
            c,
            d,
            dist,
            a1,
            b1,
            c1,
            d1,
            dist1,
            ])

Adjacent = []
for j in SegID:
    adjseg = []
    if len(j.split('-')) == 1:
        try:
```

```
        a = SegID.index(str(int(j) + 1) + '-1')
        adjseg.append(str(int(j) + 1) + '-1')
    except ValueError:
        a = 0
    try:
        a = SegID.index(str(int(j) + 2) + '-1')
        adjseg.append(str(int(j) + 2) + '-1')
    except ValueError:
        a = 0
    try:
        a = SegID.index(j + '-1')
        adjseg.append(j + '-1')
    except ValueError:
        a = 0
    for i in range(9, 1, -1):
        try:
            a = SegID.index(str(int(j) - 10) + '-' + str(i))
            adjseg.append(str(int(j) - 10) + '-' + str(i))
            break
        except ValueError:
            continue
else:
    seg = j.split('-')
```

```
if int(seg[1]) == 1:
    try:
        a = SegID.index(seg[0] + '-2')
        adjseg.append(seg[0] + '-2')
    except ValueError:
        a = 0
    try:
        a = SegID.index(str(int(int(seg[0]) / 10) * 10))
        adjseg.append(str(int(int(seg[0]) / 10) * 10))
    except ValueError:
        a = 0
else:
    try:
        a = SegID.index(seg[0] + '-' + str(int(seg[1]) - 1))
        adjseg.append(seg[0] + '-' + str(int(seg[1]) - 1))
    except ValueError:
        a = 0
    try:
        a = SegID.index(seg[0] + '-' + str(int(seg[1]) + 1))
        adjseg.append(str(int(int(seg[0]) / 10) * 10))
    except ValueError:
        try:
            a = SegID.index(seg[0] + '-' + str(int(seg[1]) + 1))
```

```
                    adjseg.append(seg[0] + '-' + str(int(seg[1]) + 1))
                except ValueError:
                    if int(seg[0]) % 10 == 0:
                        try:
                            a = SegID.index(str(int(seg[0]) + 10))
                            adjseg.append(str(int(seg[0]) + 10))
                        except ValueError:
                            a = 0
    Adjacent.append(adjseg)

copyfile('NorthAveSegmentEnergy_Intro.fzp', 'NorthAveSegmentEnergy.fzp')
CarList = []
CarFlag = []
with open('NorthAveSegmentEnergy.fzp', 'a+') as file:
#   m = 0
    with open('NorthAveCondensedData.fzp') as infile:
        for line in infile:
            f = line.split(';')
            try:
                float(f[0])
            except ValueError:
                continue
#           m += 1
```

```
#           print(m)
            t = float(f[0])
            vN = int(f[1])
            VType = f[2]
            Lat = float(f[3])
            Long = float(f[4])
            speed = float(f[5])
            accl = float(f[6])
            frac = float(f[7])
            grade = float(f[8])
            bearing = float(f[9])
            if vN not in CarList:
                CarList.append(vN)
                CarFlag.append('0')
            X = transform(dg_proj, ga_proj, Long, Lat)[0] - 2224260.0 \
                * f_m
            Y = transform(dg_proj, ga_proj, Long, Lat)[1] - 1371320.0 \
                * f_m
            segm = getSegment(
                X,
                Y,
                SegID,
                ID,
```

```
    Extreme,
    ID1,
    Extreme1,
    Adjacent,
    CarFlag[CarList.index(vN)],
    )
if segm[0] == 1:
    if bearing > 325 or bearing < 35:
        flowdir = 'WE'
    elif bearing > 145 and bearing < 215:
        flowdir = 'EW'
    elif bearing > 180:
        flowdir = 'NS'
    else:
        flowdir = 'SN'
    CarFlag[CarList.index(vN)] = segm[1]
    enchar = getEnergy(speed,accl, VType, grade,frac)
    file.write(str(t) + ';' + str(vN) + ';' + str(VType)
            + ';' + segm[1] + ';' + enchar
            + flowdir + ';\n')
```

Script 3: EnergyAnalysis. This script performs the final energy analysis and sorts the data into the proper output files

```
import numpy as np
import csv
import statistics as st
from pyproj import Proj, transform
import os
import random
import matplotlib.pyplot as plt

dg_proj = Proj(init='epsg:4269')
ga_proj = Proj(init='epsg:2240')
# feet to meter
f_m = 0.3048006096012192

dirchar=['EW','WE']
char=['PC','B','SU','TT']
EnergyChar=['Energy[kJ]','CO2[gm]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[g
m]','PM2.5[gm]','Speed[mph]','Accel[mph/s]','VSP[m^2/s^3]']
TotalTime=3600
Time=[3600]
Percent=[100]
```

```
if not os.path.exists('CSV_Summary'):
    os.makedirs('CSV_Summary')


Links=[]; LinkLength=[]
Nodes=list(map(list, zip(*(list(csv.reader(open('NorthAveNodeDetails.csv'))))[1:])))
with open("NorthAveLinkDetails.csv") as file:
    for line in file:
        f=line.split('\n')
        f=f[0].split(',')
        Links.append(f[0])
        LinkLength.append(int(f[4]))
with open("NorthAveIntersectionDetails.csv") as file:
    for line in file:
        f=line.split(',')
        Links.append(f[0])
        LinkLength.append(int(f[6]))


seg=1; breakseg=[90,140]; i=20
LinkWE=[]; LinkSegWE=[]; DistWE=[]
while i<=210:
    if i in breakseg:
        seg+=1
```

```
    j=1
    while j<=9:
        try:
            a=Links.index(str(i)+'-'+str(j))
            LinkWE.append(Links[a])
            LinkSegWE.append(seg)
            DistWE.append(LinkLength[a])
        except ValueError:
            break
        j+=1
    i+=10
    try:
        a=Links.index(str(i))
        LinkWE.append(Links[a])
        LinkSegWE.append(seg)
        DistWE.append(LinkLength[a])
    except ValueError:
        a=1

DistEW=list(reversed(DistWE));                    LinkEW=list(reversed(LinkWE));
LinkSegEW=list(reversed(LinkSegWE))
for i in range(1,len(DistWE)):
    DistWE[i]=DistWE[i-1]+DistWE[i]
```

```
    DistEW[i]=DistEW[i-1]+DistEW[i]


CarList=[]
with open("NorthAveSegmentEnergy.fzp") as infile:
    for line in infile:
        f=line.split(';')
        try:
            float(f[0])
        except ValueError:
            continue
        if not int(f[1]) in CarList:
            CarList.append(int(f[1]))


for Percentage in Percent:
    for TimeBlock in Time:
        if TimeBlock==Time[0]:
            SomeCars=random.sample(CarList,round(Percentage*len(CarList)/100))
            with open('Car_ID_'+str(Percentage)+'percent.txt','w') as f:
                for item in SomeCars:
                    f.write("%s\t" % item)
        else:
            with open('Car_ID_'+str(Percentage)+'percent.txt') as f:
                for line in f:
```

```
                y=line.split()
                SomeCars=list(map(int,y))
        energy2=[]; CarTrack=[]; AllEnergy=[];
        numen2=[]; numen_EW2=[]; numen_WE2=[]
        PartCarEW=[]; PartEnergyEW=[]; Energy_EW2=[]; PartCarWE=[]; PartEnergyWE=[]; Energy_WE2=[]
        for i in range(0,int(np.ceil(TotalTime/TimeBlock))):
            EnergySkeleton2=[]; EnergySkel2=[]
            carskel=[]; carenergy=[]
            with open("NorthAveLinkDetails.csv") as file:
                for line in file:
                    f=line.split(',')
                    EnergySkeleton2.append([i*TimeBlock,f[0],Nodes[3][Nodes[0].index(f[2])],Nodes[4][Nodes[0].index(f[2])]]+[0]+[0.0]*11)
                    EnergySkel2.append(0)
                    carenergy.append([[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]]])
                    carskel.append([[],[],[],[]])
            with open("NorthAveIntersectionDetails.csv") as file:
                for line in file:
                    f=line.split(',')
```

```
EnergySkeleton2.append([i*TimeBlock,f[0],Nodes[3][Nodes[0].index(f[2])],Nodes[4][N
odes[0].index(f[2])]]+[0]+[0.0]*11)
                EnergySkel2.append(0)

carenergy.append([[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],
[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]]])
                carskel.append([[],[],[],[]])
          AllEnergy.append(carenergy)
          energy2.append(EnergySkeleton2)
          CarTrack.append(carskel)
          numen2.append(EnergySkel2)

          EnergyEW2=[]; EnergyWE2=[]
          numenEW2=[]; numenWE2=[]
          carskelEW=[]; carskelWE=[]
          carenergyEW=[]; carenergyWE=[]
          for j in range(0,len(LinkEW)):

EnergyEW2.append([i*TimeBlock,LinkEW[j],LinkSegEW[j],DistEW[j]]+[0]+[0.0]*11)

EnergyWE2.append([i*TimeBlock,LinkWE[j],LinkSegWE[j],DistWE[j]]+[0]+[0.0]*11)
             numenEW2.append(0)
```

```
            numenWE2.append(0)

carenergyEW.append([[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],
[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]]])

carenergyWE.append([[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]],[[],[],[],[],[],
[],[],[],[],[],[]],[[],[],[],[],[],[],[],[],[],[],[]]])
            carskelEW.append([[],[],[],[]])
            carskelWE.append([[],[],[],[]])
        Energy_EW2.append(EnergyEW2); Energy_WE2.append(EnergyWE2)
        numen_EW2.append(numenEW2); numen_WE2.append(numenWE2)
        PartCarEW.append(carskelEW); PartCarWE.append(carskelWE)
        PartEnergyEW.append(carenergyEW); PartEnergyWE.append(carenergyWE)

    with open("NorthAveSegmentEnergy.fzp") as infile:
        m=0
        for line in infile:
            f=line.split(';')
            try:
                float(f[0])
            except ValueError:
                continue
            m=m+1
```

```
            print(m)
            VType=char.index(f[2])
            if int(f[1]) in SomeCars:
                i=int(np.floor(float(f[0])/TimeBlock)); j=Links.index(f[3])
                if int(f[1]) not in CarTrack[i][j][VType]:
                    CarTrack[i][j][VType].append(int(f[1]))
                    for k in range(0,8):
                            AllEnergy[i][j][VType][k].append(float(f[k+4]))
                    for k in range(8,11):
                        AllEnergy[i][j][VType][k].append([float(f[k+4])])
                else:
                    for k in range(0,8):

AllEnergy[i][j][VType][k][CarTrack[i][j][VType].index(int(f[1]))]+=float(f[k+4])
                    for k in range(8,11):

AllEnergy[i][j][VType][k][CarTrack[i][j][VType].index(int(f[1]))].append(float(f[k+4]))
                if (f[15]=='EW' or f[15]=='WE') and f[3] in LinkWE:
                    exec('j=Link'+f[15]+'.index(f[3])')
                    exec('CT=PartCar'+f[15]); exec('AE=PartEnergy'+f[15])
                    if int(f[1]) not in CT[i][j][VType]:
                        CT[i][j][VType].append(int(f[1]))
                        for k in range(0,8):
```

```
                    AE[i][j][VType][k].append(float(f[k+4]))
                for k in range(8,11):
                    AE[i][j][VType][k].append([float(f[k+4])])
            else:
                for k in range(0,8):
                    AE[i][j][VType][k][CT[i][j][VType].index(int(f[1]))]+=float(f[k+4])
                for k in range(8,11):

AE[i][j][VType][k][CT[i][j][VType].index(int(f[1]))].append(float(f[k+4]))
            exec('PartCar'+f[15]+'=CT'); exec('PartEnergy'+f[15]+'=AE')


    for k in range(0, len(char)):
        energy=[]; energy1=[]
        for i in range(0,int(np.ceil(TotalTime/TimeBlock))):
            EnergySkeleton=[]; EnergySkeleton1=[]
            with open("NorthAveLinkDetails.csv") as file:
                for line in file:
                    f=line.split(',')

EnergySkeleton.append([i*TimeBlock,f[0],Nodes[3][Nodes[0].index(f[2])],Nodes[4][No
des[0].index(f[2])]]+[0]+[0.0]*11)
```

```
EnergySkeleton1.append([i*TimeBlock,f[0],Nodes[3][Nodes[0].index(f[2])],Nodes[4][N
odes[0].index(f[2])]]+[0]+[0.0]*11)
        with open("NorthAveIntersectionDetails.csv") as file:
          for line in file:
            f=line.split(',')

EnergySkeleton.append([i*TimeBlock,f[0],Nodes[3][Nodes[0].index(f[2])],Nodes[4][No
des[0].index(f[2])]]+[0]+[0.0]*11)

EnergySkeleton1.append([i*TimeBlock,f[0],Nodes[3][Nodes[0].index(f[2])],Nodes[4][N
odes[0].index(f[2])]]+[0]+[0.0]*11)
        energy.append(EnergySkeleton); energy1.append(EnergySkeleton1)

      for i in range(0,len(energy2)):
        for j in range(0, len(energy2[i])):
          if len(CarTrack[i][j][k])>0:
            for l in range(0,8):
              energy[i][j][l+5]=st.mean(AllEnergy[i][j][k][l])
              energy1[i][j][l+5]=st.pstdev(AllEnergy[i][j][k][l])
              energy2[i][j][l+5]+=sum(AllEnergy[i][j][k][l])
            for l in range(8,11):
              lis=[]
```

```
                for x in AllEnergy[i][j][k][l]:
                    lis+= x
                energy[i][j][l+5]=st.mean(lis)
                energy1[i][j][l+5]=st.pstdev(lis)
                energy2[i][j][l+5]+=sum(lis)
            numen2[i][j]+=len(lis)
            energy2[i][j][4]+=len(AllEnergy[i][j][k][l])
            energy[i][j][4]=len(AllEnergy[i][j][k][l])
            energy1[i][j][4]=len(AllEnergy[i][j][k][l])
        else:
            for l in range(0,11):
                energy[i][j][l+5]='N/A'
                energy1[i][j][l+5]='N/A'


NetEnergy=[['Time[s]','SegmentID','Latitude','Longitude','#vehicles','Energy[kJ]','CO2[g
m]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Ac
cel[mph/s]','VSP[m^2/s^3]']]
    for i in range(0,len(energy)):
        NetEnergy.extend(energy[i])
```

```
    with
open('./CSV_Summary/Average_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBloc
k)+'sec_'+char[k]+'.csv', 'w',newline='') as f:
        writer = csv.writer(f)
        writer.writerows(NetEnergy)



NetEnergy=[['Time[s]','SegmentID','Latitude','Longitude','#vehicles','Energy[kJ]','CO2[g
m]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Ac
cel[mph/s]','VSP[m^2/s^3]']]
    for i in range(0,len(energy1)):
        NetEnergy.extend(energy1[i])

    with
open('./CSV_Summary/SD_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBlock)+'s
ec_'+char[k]+'.csv', 'w',newline='') as f:
        writer = csv.writer(f)
        writer.writerows(NetEnergy)



NetEnergy=[['Time[s]','SegmentID','Latitude','Longitude','#vehicles','Energy[kJ]','CO2[g
```

```
m]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Ac
cel[mph/s]','VSP[m^2/s^3]']]
    for i in range(0,len(energy2)):
      NetEnergy.extend(energy2[i])


    with
open('./CSV_Summary/Total_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBlock)+
'sec_AllVehicles.csv', 'w',newline='') as f:
      writer = csv.writer(f)
      writer.writerows(NetEnergy)


    for i in range(0,len(energy2)):
      for j in range(0, len(energy2[i])):
        if energy2[i][j][4]>0:
          for l in range(0,8):
            energy2[i][j][l+5]=energy2[i][j][l+5]/energy2[i][j][4]
          for l in range(8,11):
            energy2[i][j][l+5]=energy2[i][j][l+5]/numen2[i][j]
        else:
          for l in range(0,11):
            energy2[i][j][l+5]='N/A'
```

```
NetEnergy=[['Time[s]','SegmentID','Latitude','Longitude','#vehicles','Energy[kJ]','CO2[g
m]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Ac
cel[mph/s]','VSP[m^2/s^3]']]
    for i in range(0,len(energy2)):
        NetEnergy.extend(energy2[i])

    with
open('./CSV_Summary/Average_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBloc
k)+'sec_AllVehicles.csv', 'w',newline='') as f:
        writer = csv.writer(f)
        writer.writerows(NetEnergy)

    for dirn in dirchar:
        exec('link=Link'+dirn); exec('linkseg=LinkSeg'+dirn); exec('dist=Dist'+dirn)
        exec('energy2=Energy_'+dirn+'2');            exec('AllEnergy=PartEnergy'+dirn);
exec('CarTrack=PartCar'+dirn); exec('numen2=numen_'+dirn+'2')
        for k in range(0, len(char)):
            energy=[]; energy1=[]
            for i in range(0,int(np.ceil(TotalTime/TimeBlock))):
                Energy=[]; Energy1=[]
                for j in range(0,len(link)):
                    Energy.append([i*TimeBlock,link[j],linkseg[j],dist[j]]+[0]+[0.0]*11)
```

```
        Energy1.append([i*TimeBlock,link[j],linkseg[j],dist[j]]+[0]+[0.0]*11)
    energy.append(Energy); energy1.append(Energy1)

for i in range(0,len(energy2)):
    for j in range(0, len(energy2[i])):
        if len(CarTrack[i][j][k])>0:
            for l in range(0,8):
                energy[i][j][l+5]=st.mean(AllEnergy[i][j][k][l])
                energy1[i][j][l+5]=st.pstdev(AllEnergy[i][j][k][l])
                energy2[i][j][l+5]+=sum(AllEnergy[i][j][k][l])
            for l in range(8,11):
                lis=[]
                for x in AllEnergy[i][j][k][l]:
                    lis+= x
                energy[i][j][l+5]=st.mean(lis)
                energy1[i][j][l+5]=st.pstdev(lis)
                energy2[i][j][l+5]+=sum(lis)
            numen2[i][j]+=len(lis)
            energy2[i][j][4]+=len(AllEnergy[i][j][k][l])
            energy[i][j][4]=len(AllEnergy[i][j][k][l])
            energy1[i][j][4]=len(AllEnergy[i][j][k][l])
        else:
            for l in range(0,11):
```

```
                    energy[i][j][l+5]='N/A'
                    energy1[i][j][l+5]='N/A'


NetEnergy=[['Time[s]','SegmentID','LinkSeg','Distance[ft]','#vehicles','Energy[kJ]','CO2[gm]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Accel[mph/s]','VSP[m^2/s^3]']]
        for i in range(0,len(energy)):
            NetEnergy.extend(energy[i])

        with open('./CSV_Summary/Average_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBlock)+'sec_'+char[k]+'_'+dirn+'.csv', 'w',newline='') as f:
            writer = csv.writer(f)
            writer.writerows(NetEnergy)



NetEnergy=[['Time[s]','SegmentID','LinkSeg','Distance[ft]','#vehicles','Energy[kJ]','CO2[gm]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Accel[mph/s]','VSP[m^2/s^3]']]
        for i in range(0,len(energy1)):
            NetEnergy.extend(energy1[i])
```

```
                with
open('./CSV_Summary/SD_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBlock)+'s
ec_'+char[k]+'_'+dirn+'.csv', 'w',newline='') as f:
                    writer = csv.writer(f)
                    writer.writerows(NetEnergy)



NetEnergy=[['Time[s]','SegmentID','LinkSeg','Distance[ft]','#vehicles','Energy[kJ]','CO2[
gm]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','A
ccel[mph/s]','VSP[m^2/s^3]']]
            for i in range(0,len(energy2)):
                NetEnergy.extend(energy2[i])

            with
open('./CSV_Summary/Total_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBlock)+
'sec_AllVehicles'+'_'+dirn+'.csv', 'w',newline='') as f:
                writer = csv.writer(f)
                writer.writerows(NetEnergy)

            for i in range(0,len(energy2)):
                for j in range(0, len(energy2[i])):
                    if energy2[i][j][4]>0:
```

```
                for l in range(0,8):
                    energy2[i][j][l+5]=energy2[i][j][l+5]/energy2[i][j][4]
                for l in range(8,11):
                    energy2[i][j][l+5]=energy2[i][j][l+5]/numen2[i][j]
            else:
                for l in range(0,11):
                    energy2[i][j][l+5]='N/A'


NetEnergy=[['Time[s]','SegmentID','LinkSeg','Distance[ft]','#vehicles','Energy[kJ]','CO2[gm]','HC[gm]','CO[gm]','NOX[gm]','VOC[gm]','PM10[gm]','PM2.5[gm]','Speed[mph]','Accel[mph/s]','VSP[m^2/s^3]']]
    for i in range(0,len(energy2)):
        NetEnergy.extend(energy2[i])

    with open('./CSV_Summary/Average_Energy_'+str(Percentage)+'percent_veh_'+str(TimeBlock)+'sec_AllVehicles'+'_'+dirn+'.csv', 'w',newline='') as f:
        writer = csv.writer(f)
        writer.writerows(NetEnergy)
```

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